CARBON, COVER AND CLOUDS: UPDATE FROM ONE CORNER OF THE LANDSAT TIME-SERIES LANDSCAPE

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USGS science for a changing world

USDA United States Department of Agriculture National Institute of Food and Agriculture

NASA Carbon Monitoring System

Overall Project Goal

Goal 1: Consistency between change and cover

Change

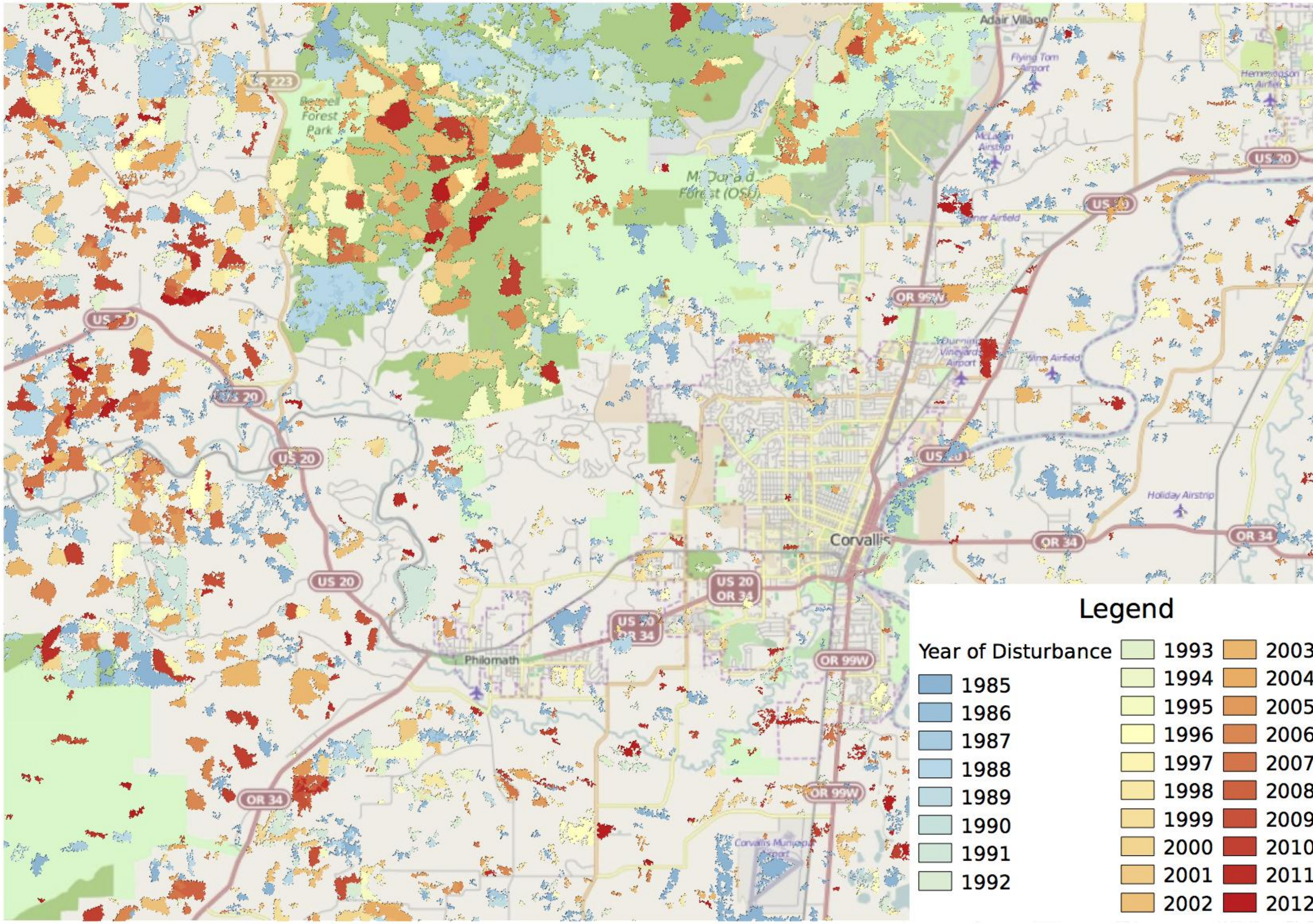
Monitoring System

Cover

Goal 2: Flexible methods to paint any land cover map through time

Localizeable

Localizeable


Adair Village
OR 223
US 20
OR 99W
OR 34
US 20 OR 34
Corvallis
Philomath
Holiday Airstrip
Legend
Year of Disturbance
1985
1986
1987
1988
1989
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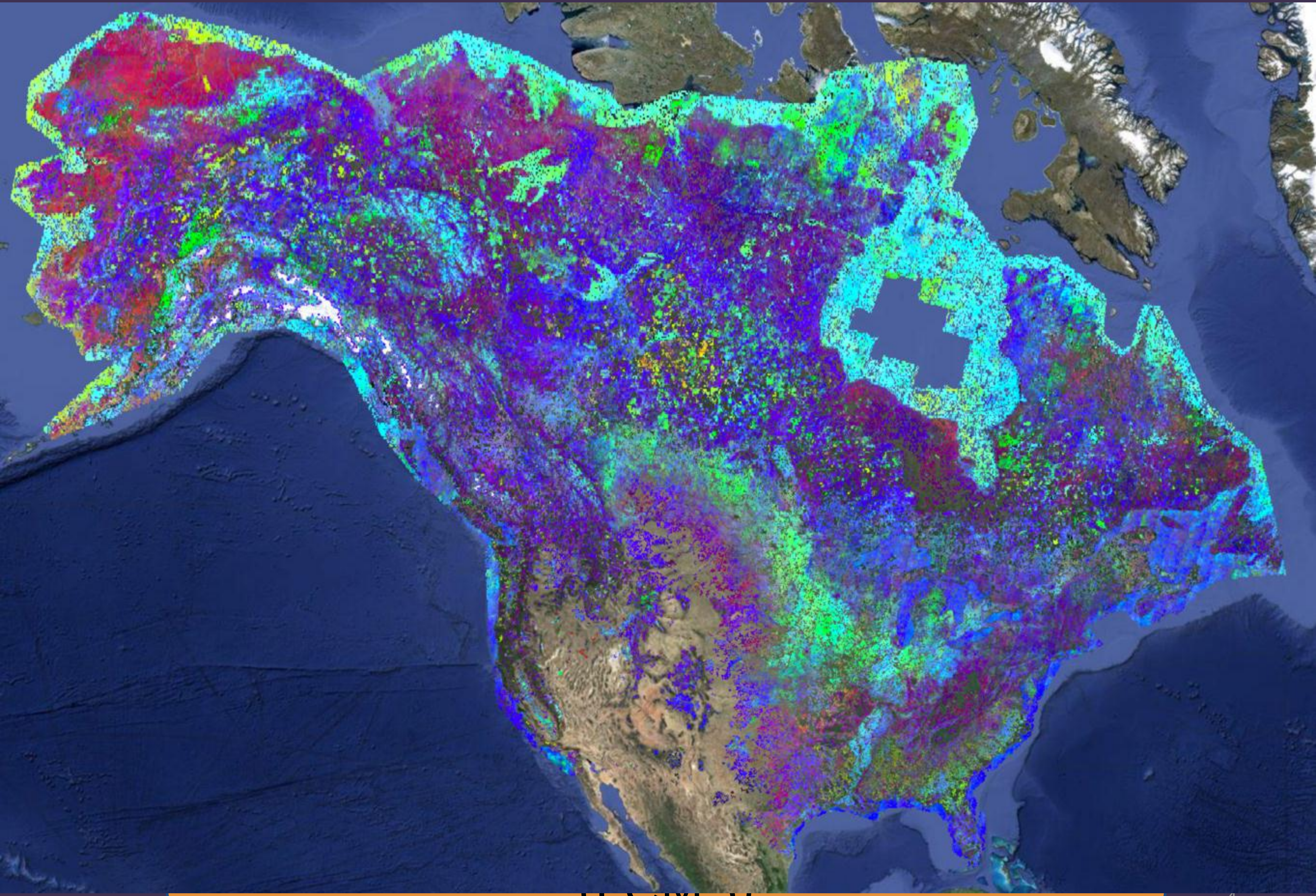


(LCMS)

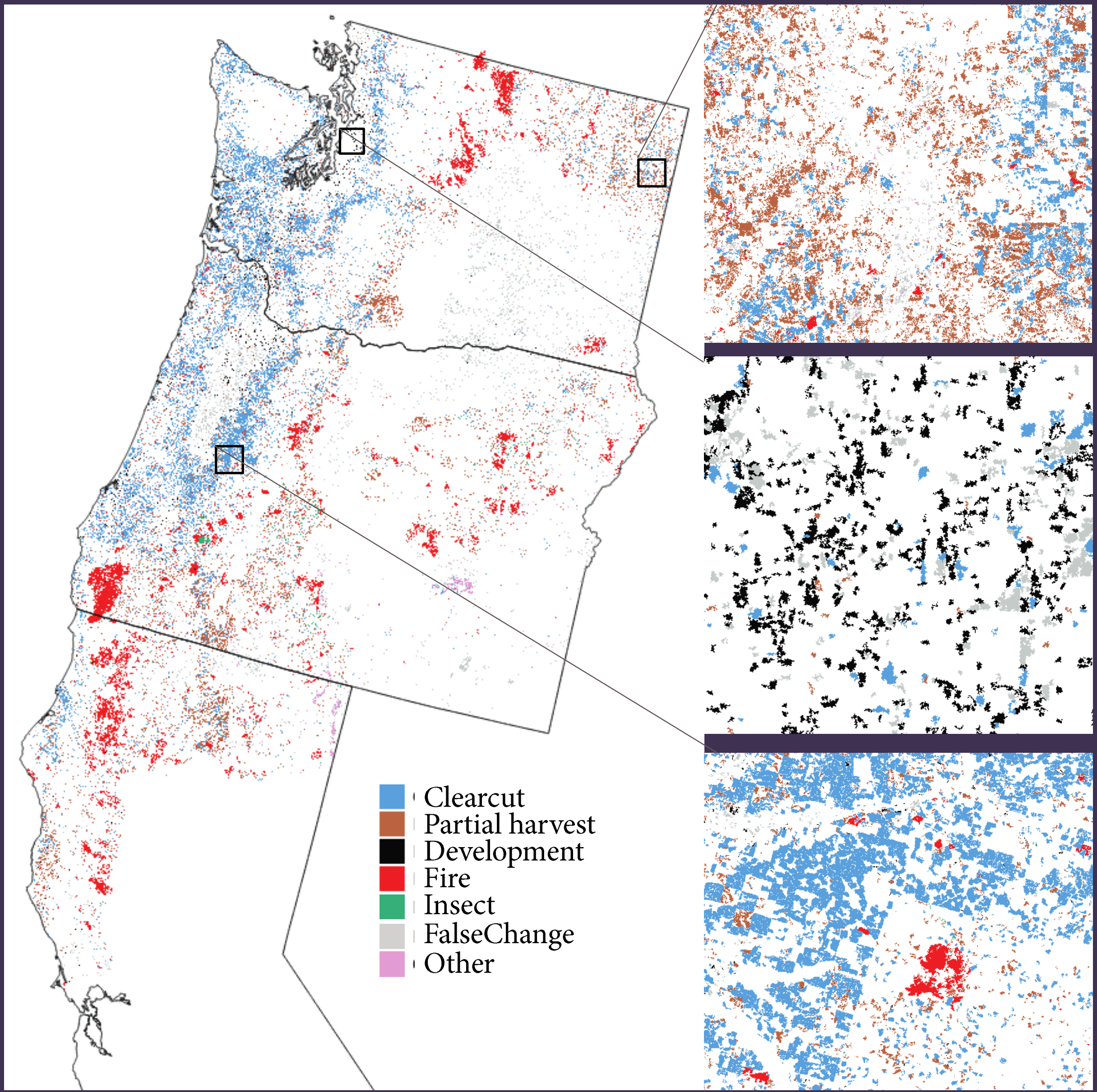
Agents of change

Patch-based

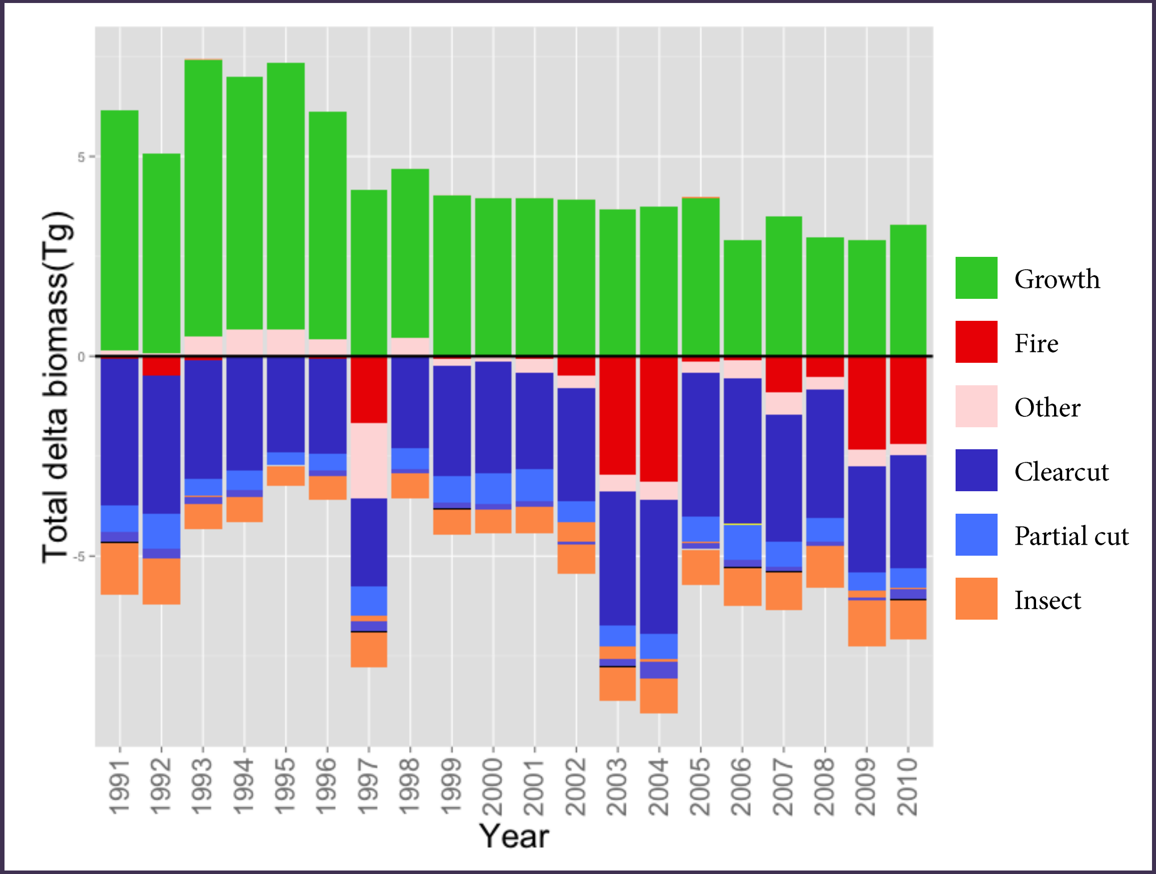
Human-trained

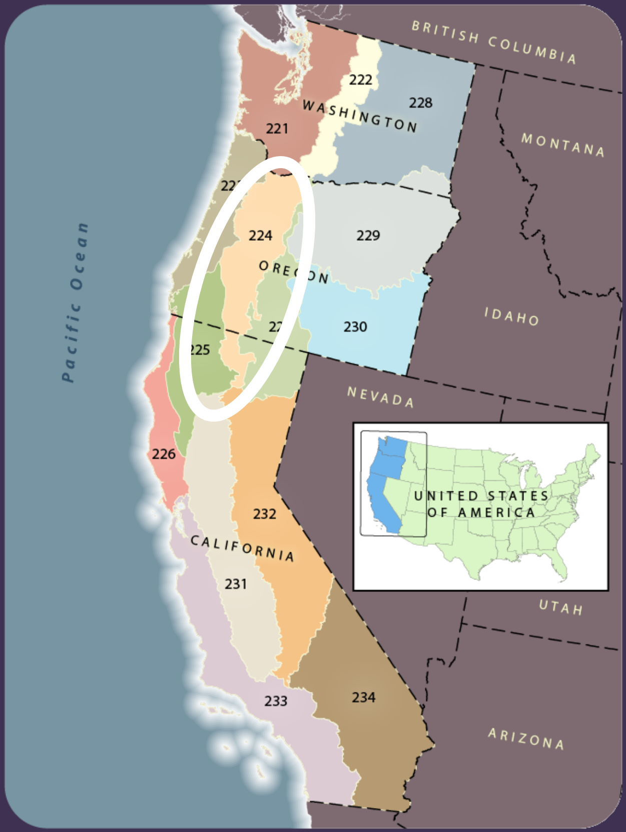
Machine- learned

Contextual

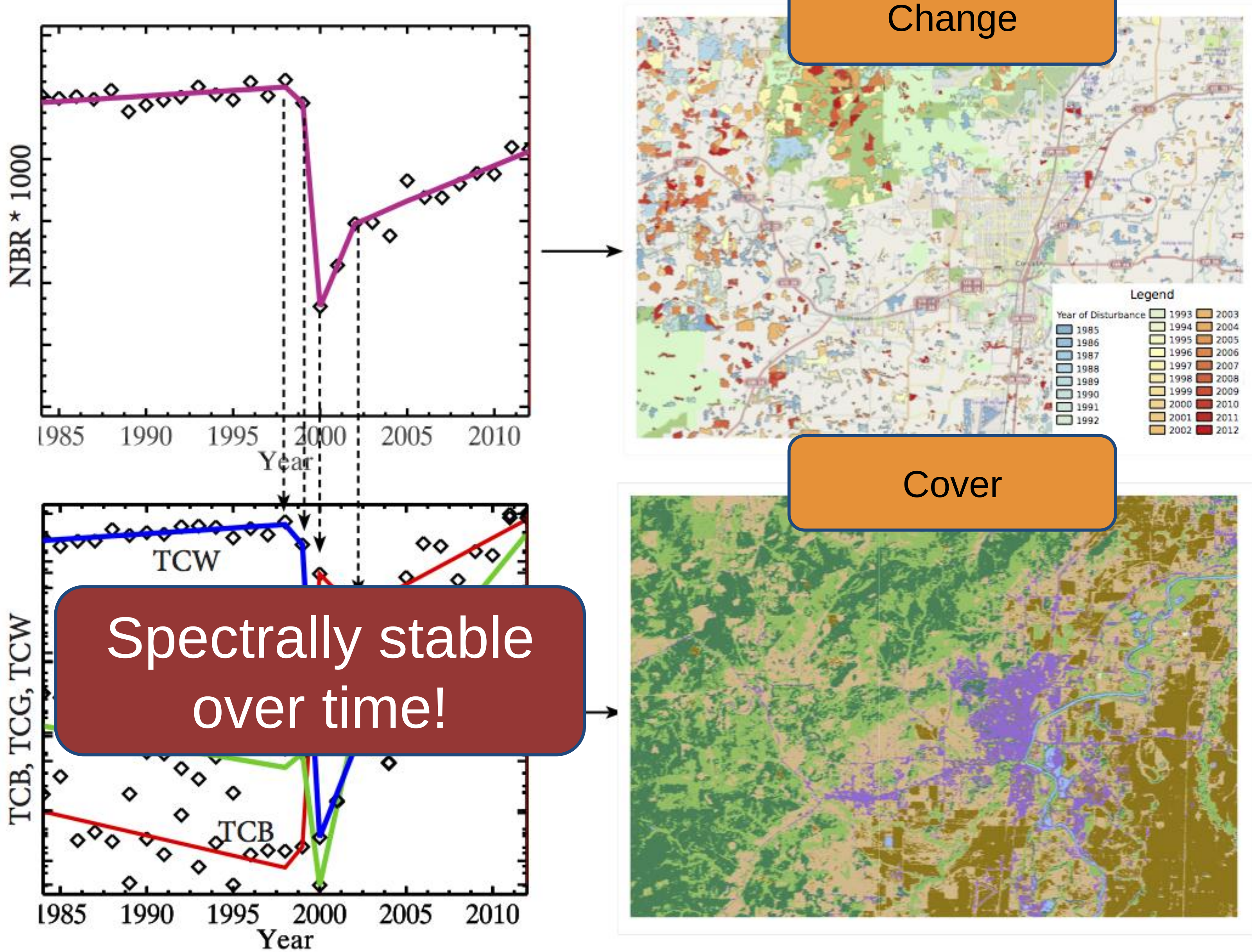


Biomass change by agent





For the West Cascades Province, anthropogenic agents drive carbon loss in most years

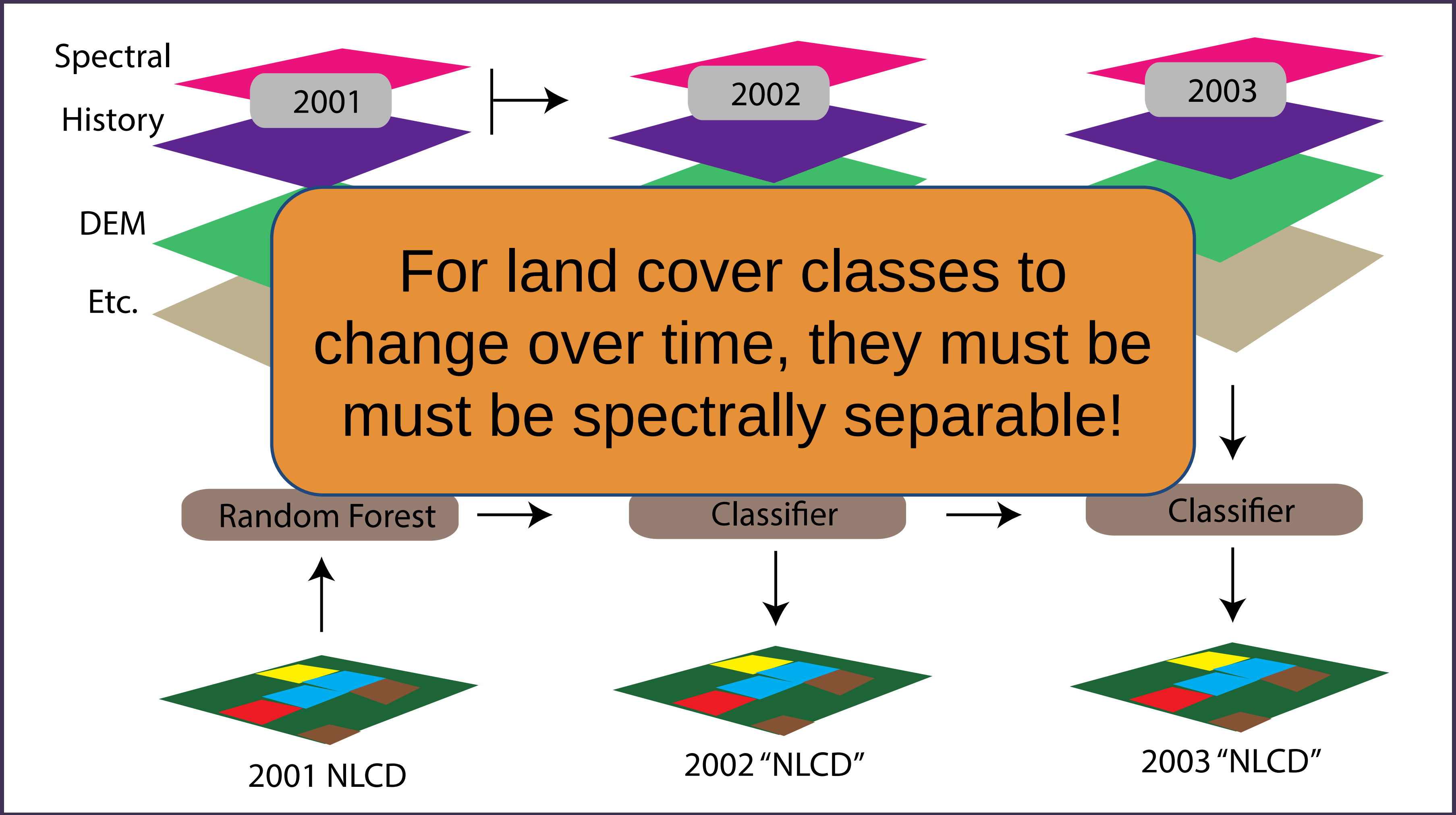


Change

Cover

Spectrally stable over time!

A KEY CONSTRAINT!



A Possible Conflict

Land cover classes must be spectrally separable!

Many land cover maps have classes that are NOT spectrally separable!

User: "I want to use my own land cover map!"

Classification Scheme Preservation vs. Classifier Accuracy

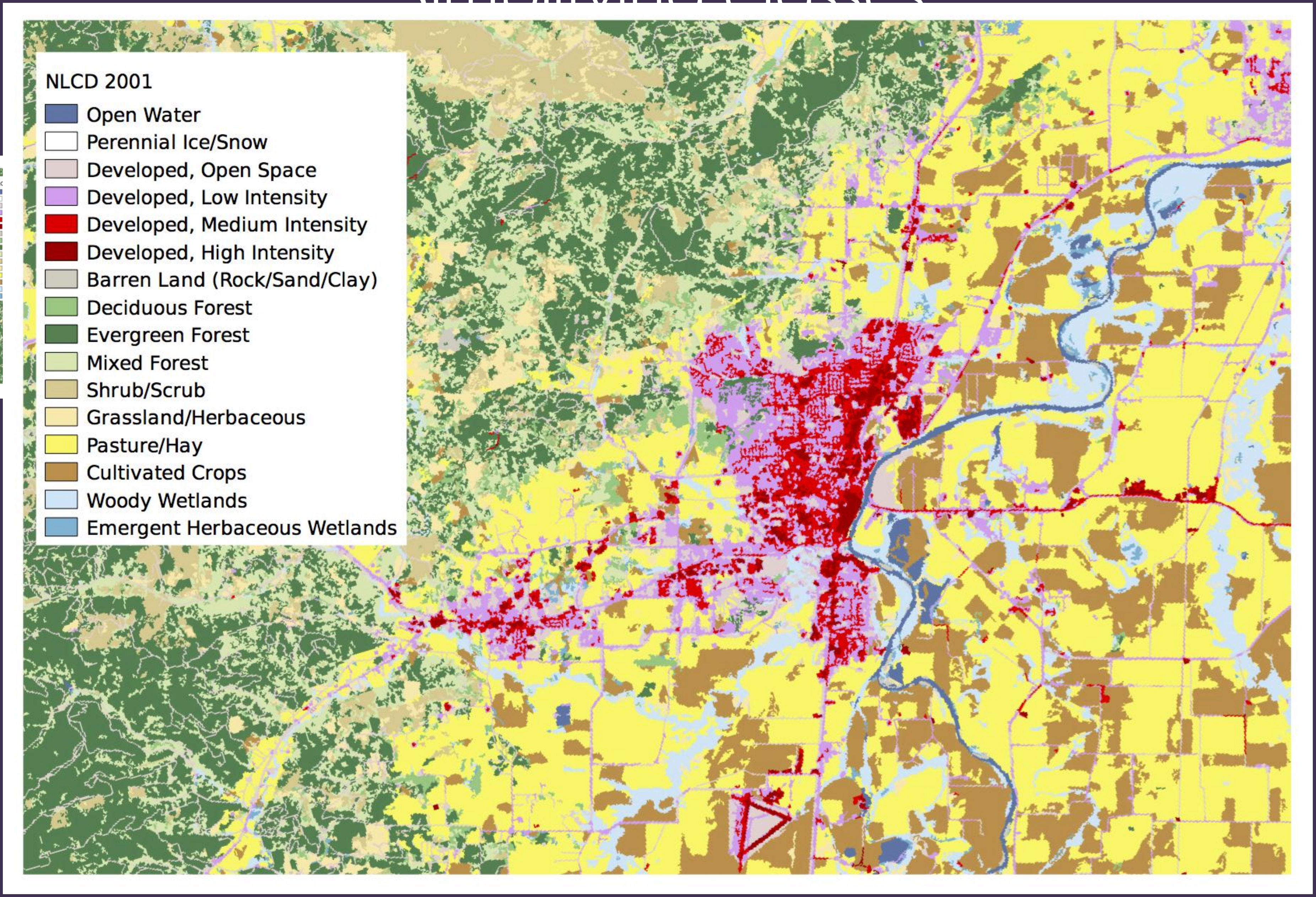
Faithful to original scheme

Accurate

Increase spectral information depth

Re-map classes to spectrally separable

Simplifying classes



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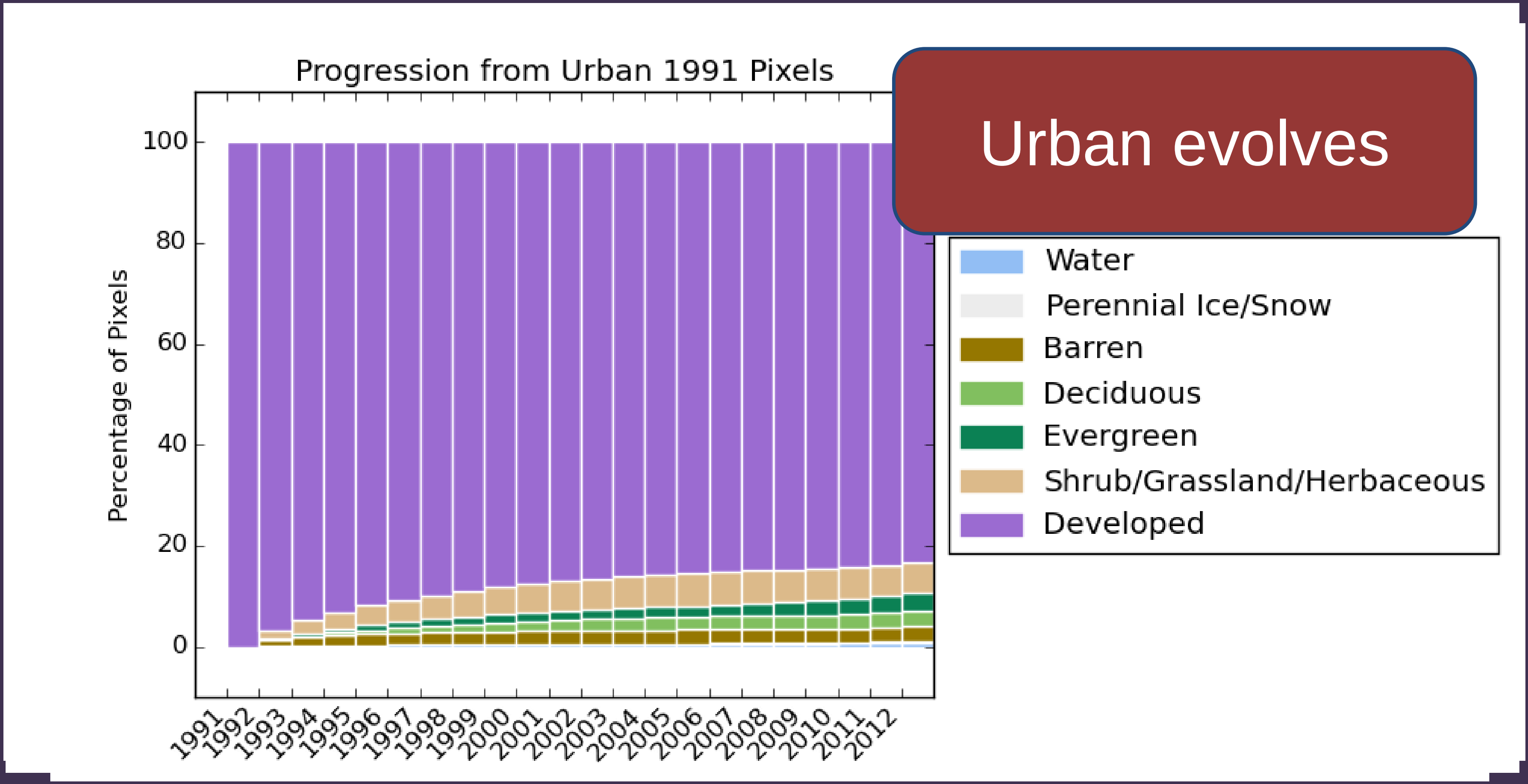
Summaries by type



Accuracy: Comparing to 2001 map

		LT random forest classes							
		Open water	Perennial ice/snow	Developed medium-high intensity	Barren	Deciduous-mixed forest	Evergreen forest	Herbaceous-shrub	Producer's accuracy
Reference revised Land cover classes	Open water	1057	10	44	36	2	23	13	***0.89***
	Perennial ice/snow	0	89	0	6	1	2	2	***0.89***
	Developed medium-high intensity	10	0	1330	92	4	20	126	***0.84***
	Barren	117	93	1163	5574	107	143	1089	***0.67***
	Deciduous-mixed forest	2	19	56	28	3121	1133	634	***0.63***
	Evergreen forest	74	9	136	308	1380	23642	1959	***0.86***
	Herbaceous-shrub	79	32	1139	10808	928	3117	33201	***0.67***
	User's accuracy	***0.78***	***0.35***	***0.34***	***0.33***	***0.56***	***0.84***	***0.9***	**0.73**

Some classes still poorly modeled

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Issues:

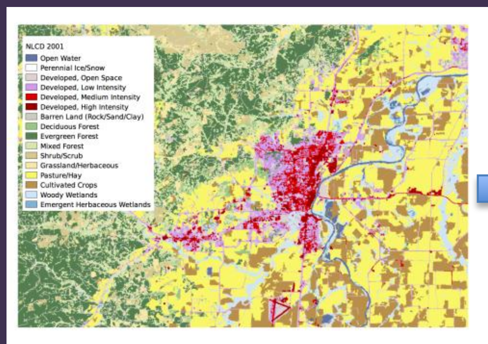
Weak classes:

Some classes are very poorly modeled - can additional dates of imagery help?

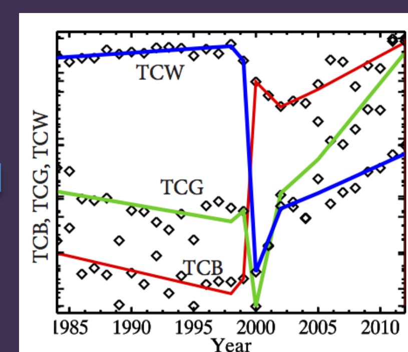
Classification logic:

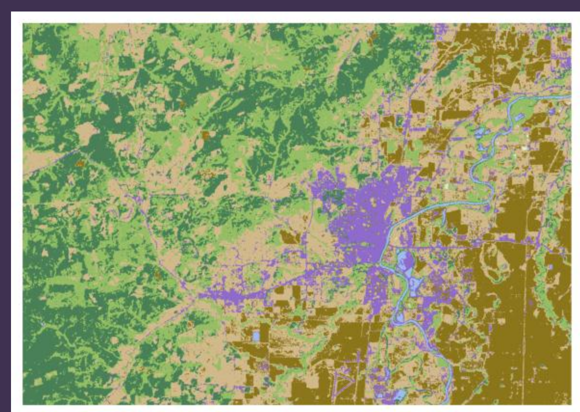
Simplification step is actually another classification – can we eliminate this step?

Simplify process for testing



Train





Future direction

1. Add phenologically important dates (**Spring**)

2. Quantify tradeoff between simplicity & accuracy

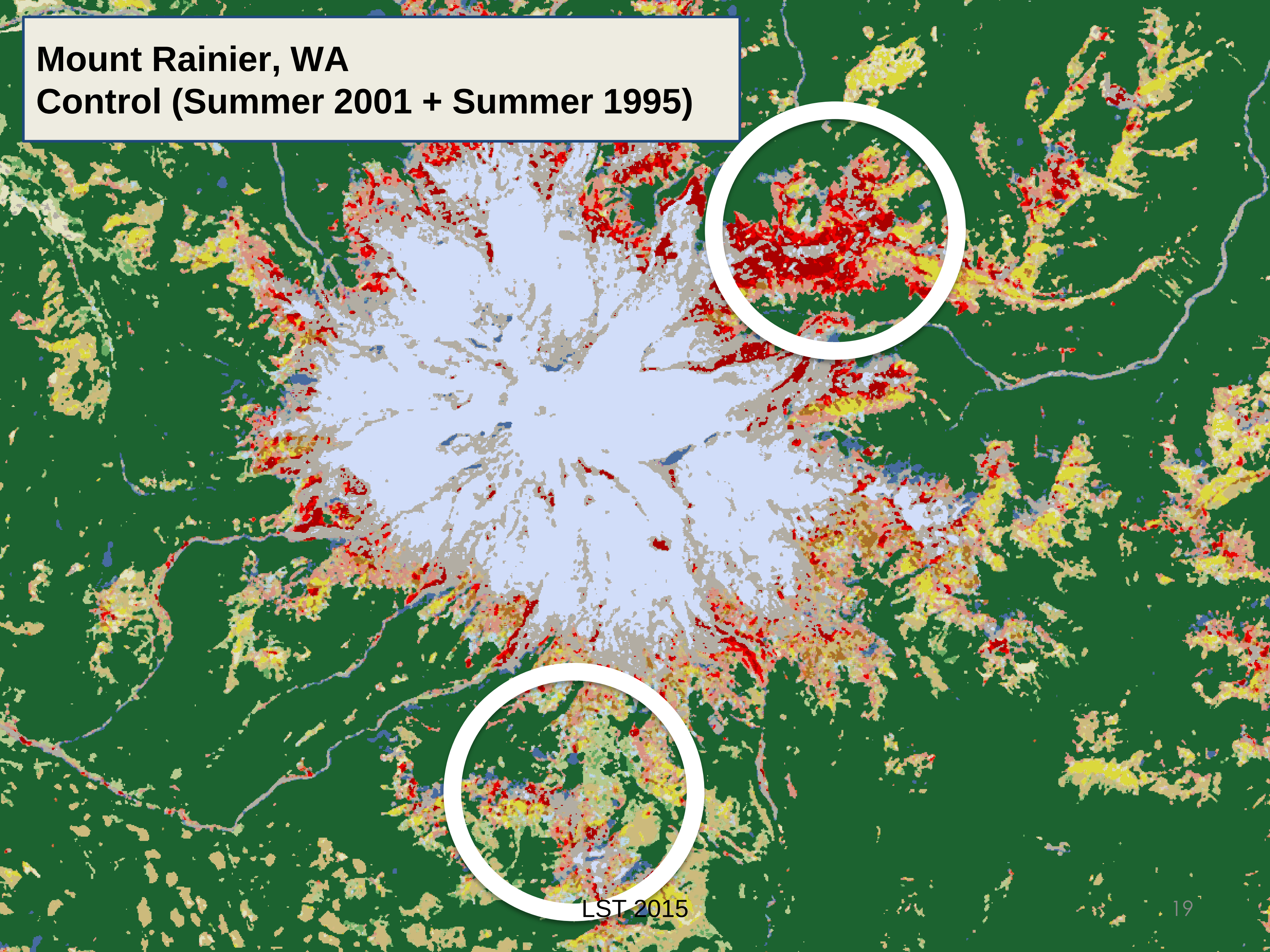
1. Improve L8 cloud masking

2. Include **patch** characteristics: Size, Shape, Texture

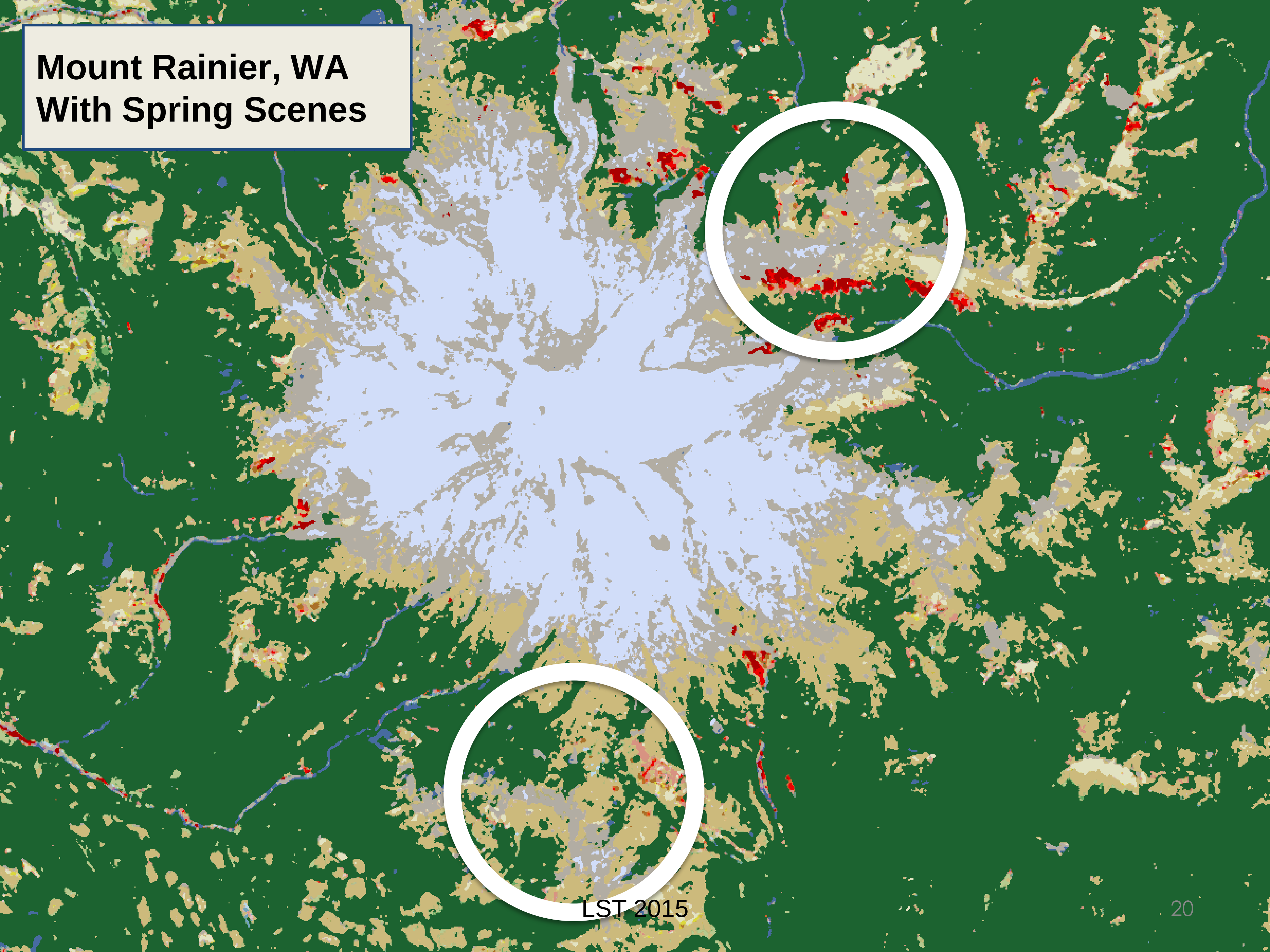
Future directions

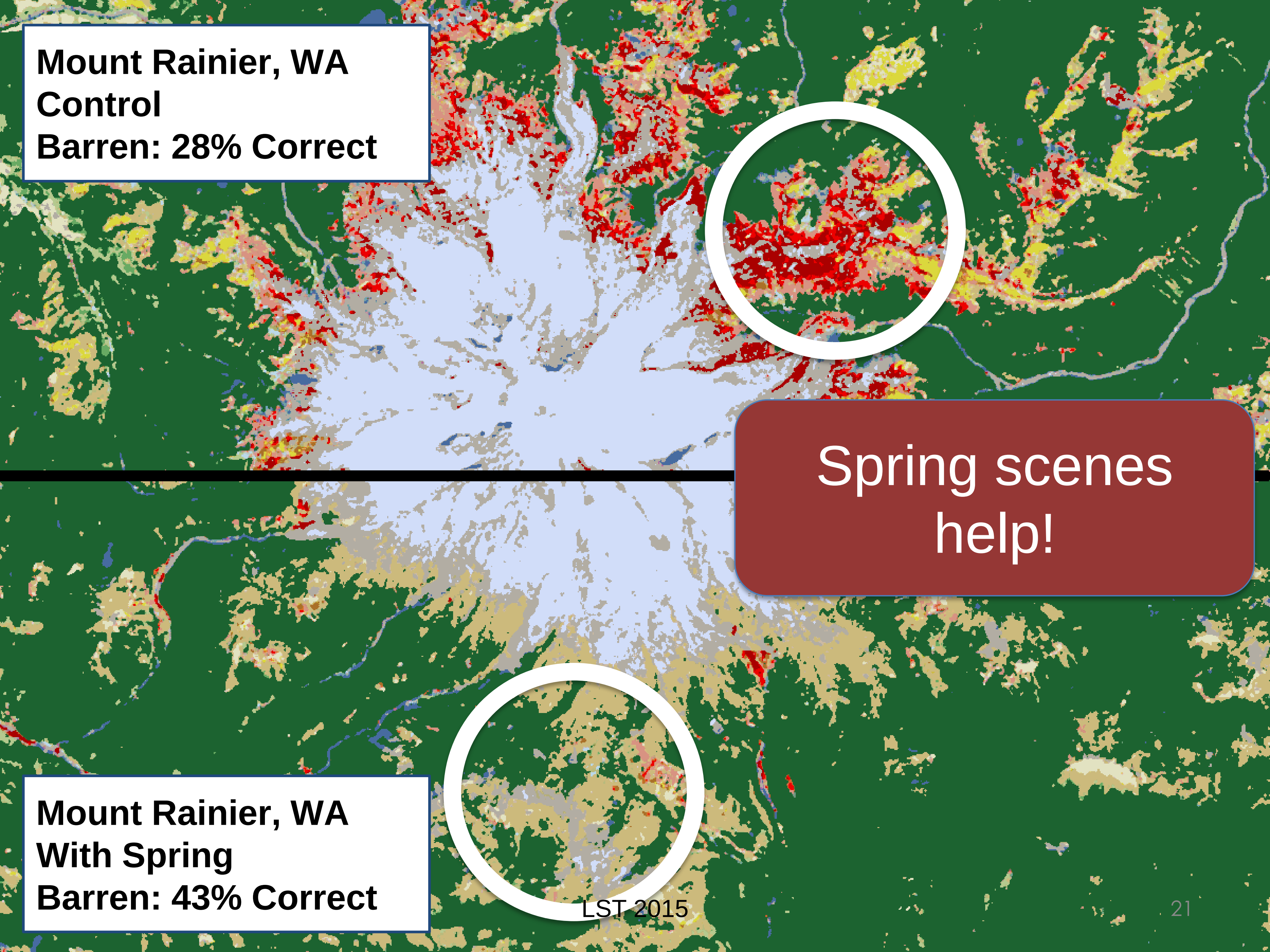
1. Add phenologically important dates (**Spring**)
2. Quantify tradeoff between simplicity & accuracy
3. Improve L8 cloud masking
4. Include **patch** characteristics: Size, Shape, Texture

Mount Rainier, WA
Control (Summer 2001 + Summer 1995)



Mount Rainier, WA
With Spring Scenes



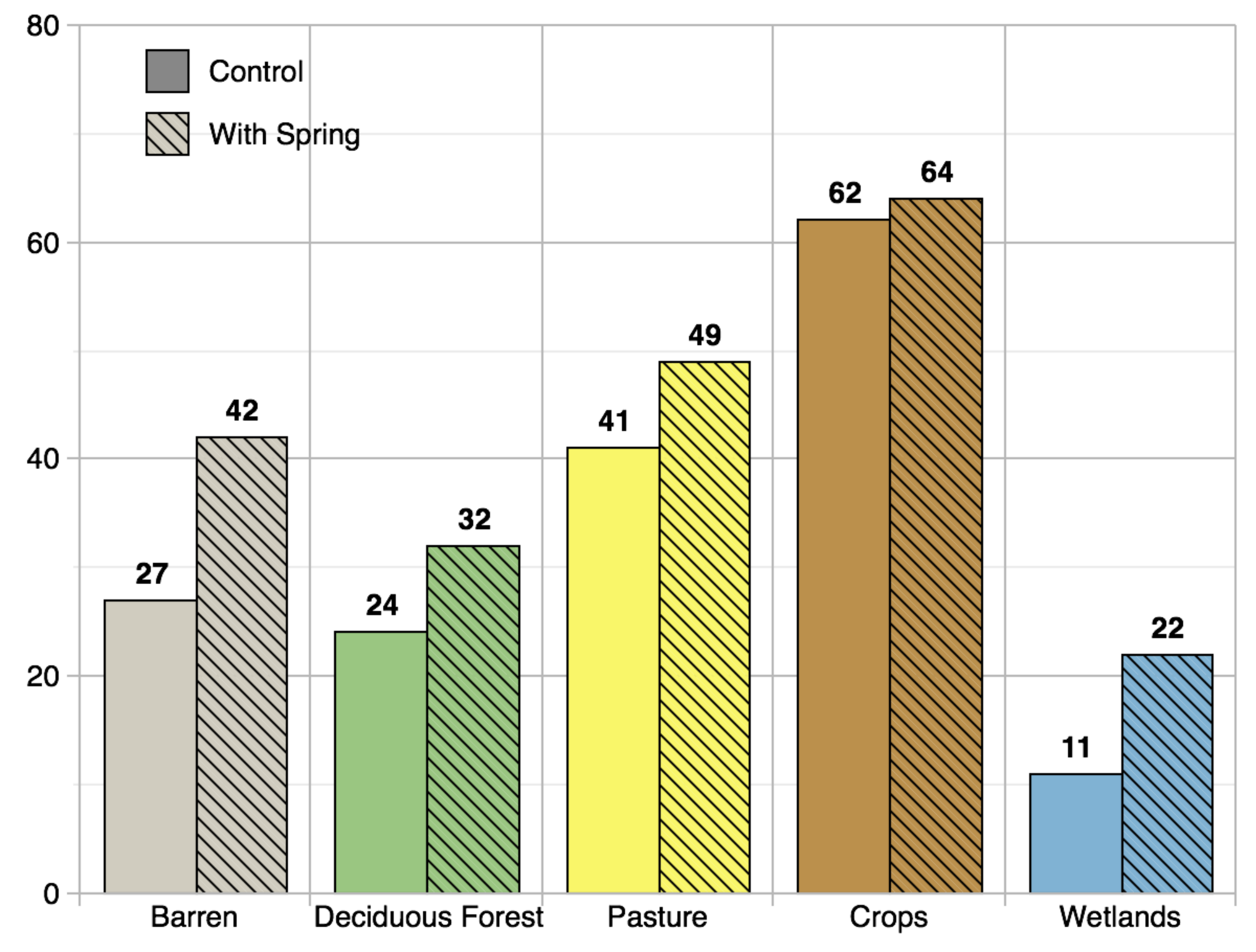


Mount Rainier, WA
Control
Barren: 28% Correct

Spring scenes help!

Mount Rainier, WA
With Spring
Barren: 43% Correct

Accuracy improvement



Future directions

1. Add phenologically important dates (**Spring**)

2. Quantify tradeoff between simplicity & accuracy

1. Improve L8 cloud masking

2. Include **patch** characteristics: Size, Shape, Texture

Classification Scheme Preservation vs. Classifier Accuracy

Not all classes in, e.g. NLCD, are spectrally separable.

We want to **choose a simpler scheme** (remap a subset of classes) that:

1. remains **Faithful** to the original scheme

2. gives **Accurate** labels from satellite imagery

Classification Scheme Preservation vs. Classifier Accuracy

1. Scheme Fidelity

2. Classifier Accuracy

$$\max_{s \subseteq N} F(s) + \lambda\, Acc(s)$$

Choose a subset of the original scheme

Explicit Tradeoff

Formalizing Suggests Solutions, Highlights Challenges

Pros

Cons

General optimization algorithms exist

Classification scheme similarity metrics underexplored

Tradeoffs must be explicit

Future directions

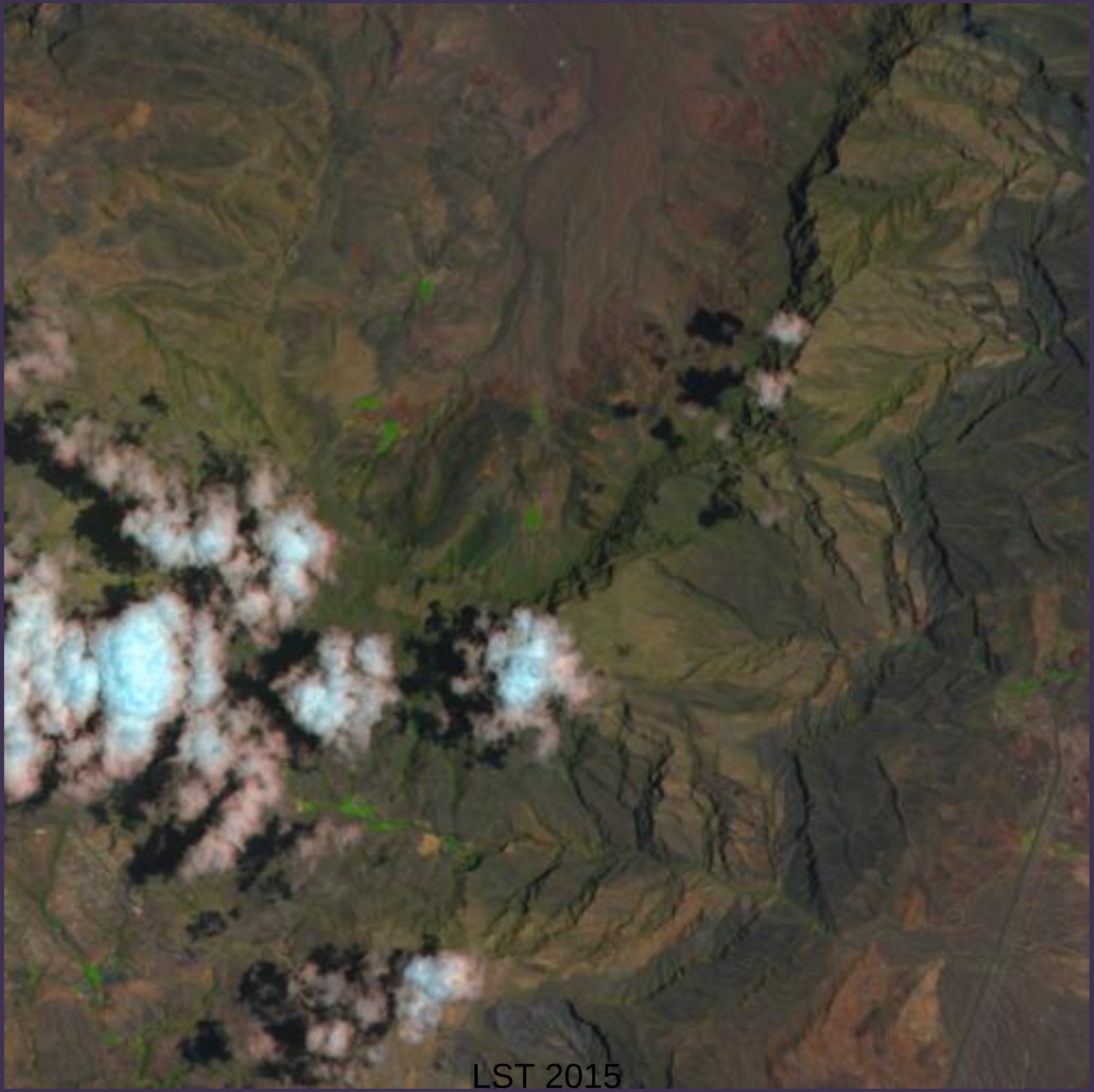
1. Add phenologically important dates (**Spring**)

2. Omit class simplification step

1. Improve L8 cloud masking

2. Include **patch** characteristics: Size, Shape, Texture

Extend SPARCS to Landsat 8



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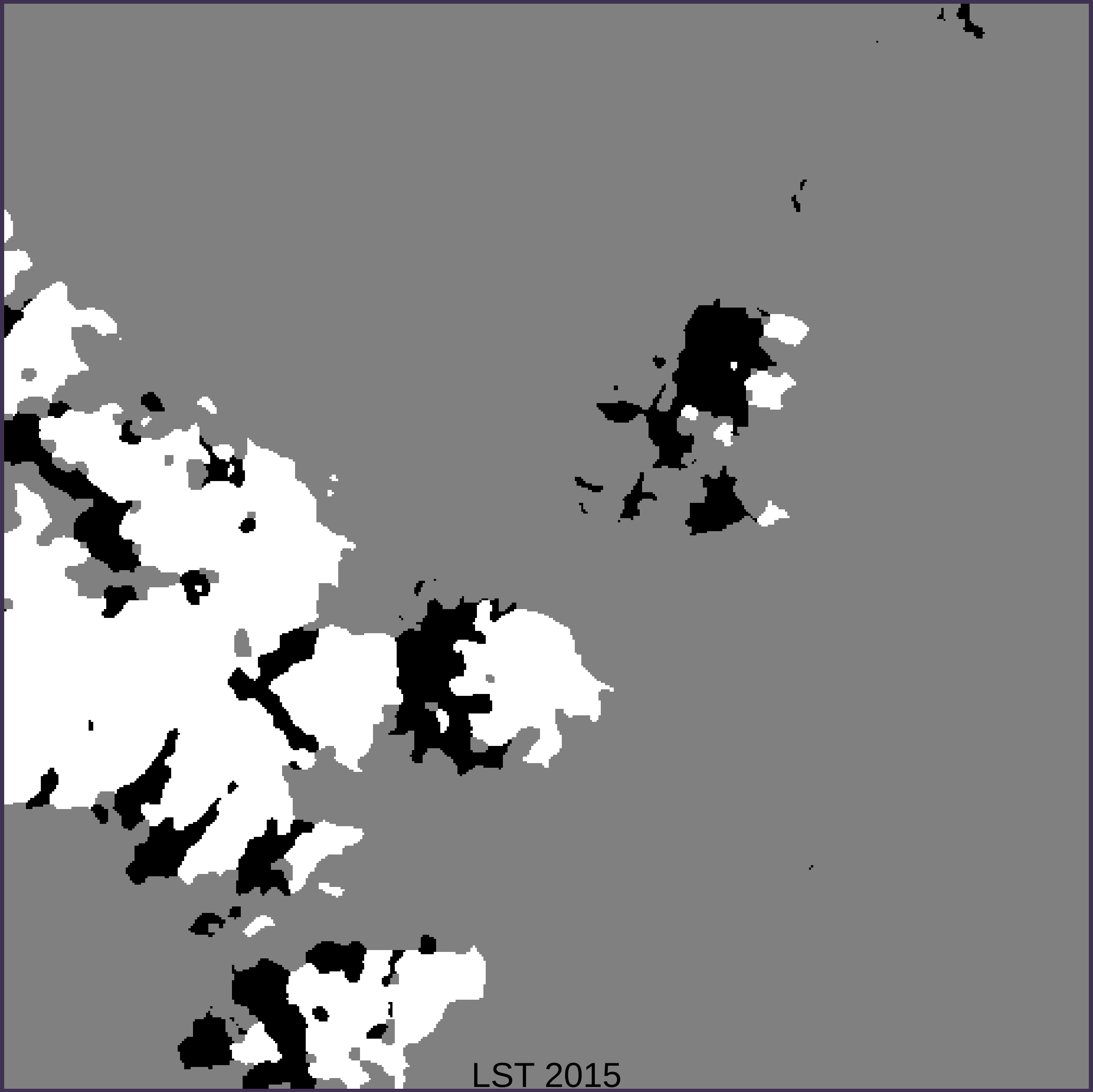
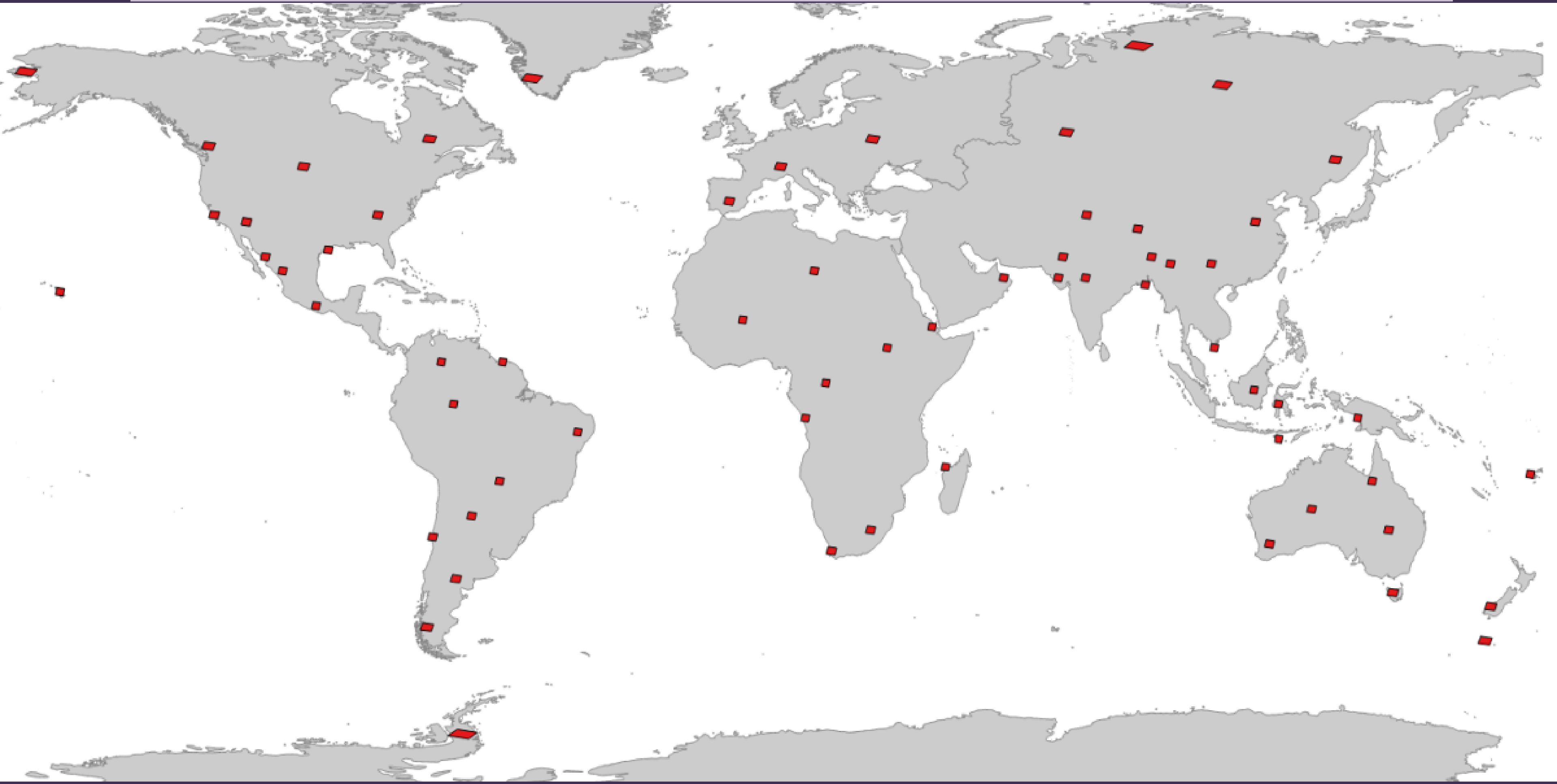
Extend SPARCS to Landsat 8 (v0.1)



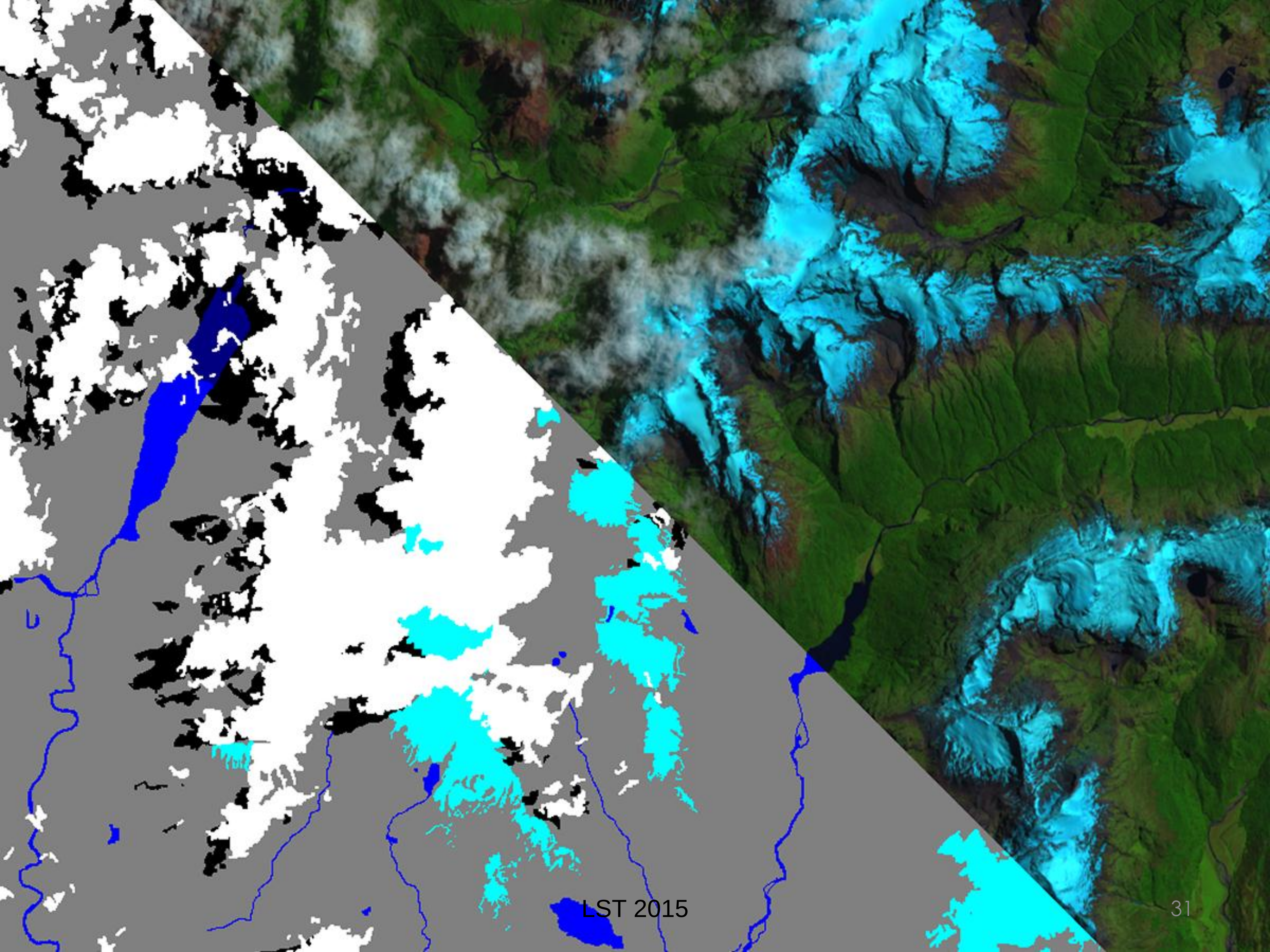
Landsat 8 Cloud Masking Dataset

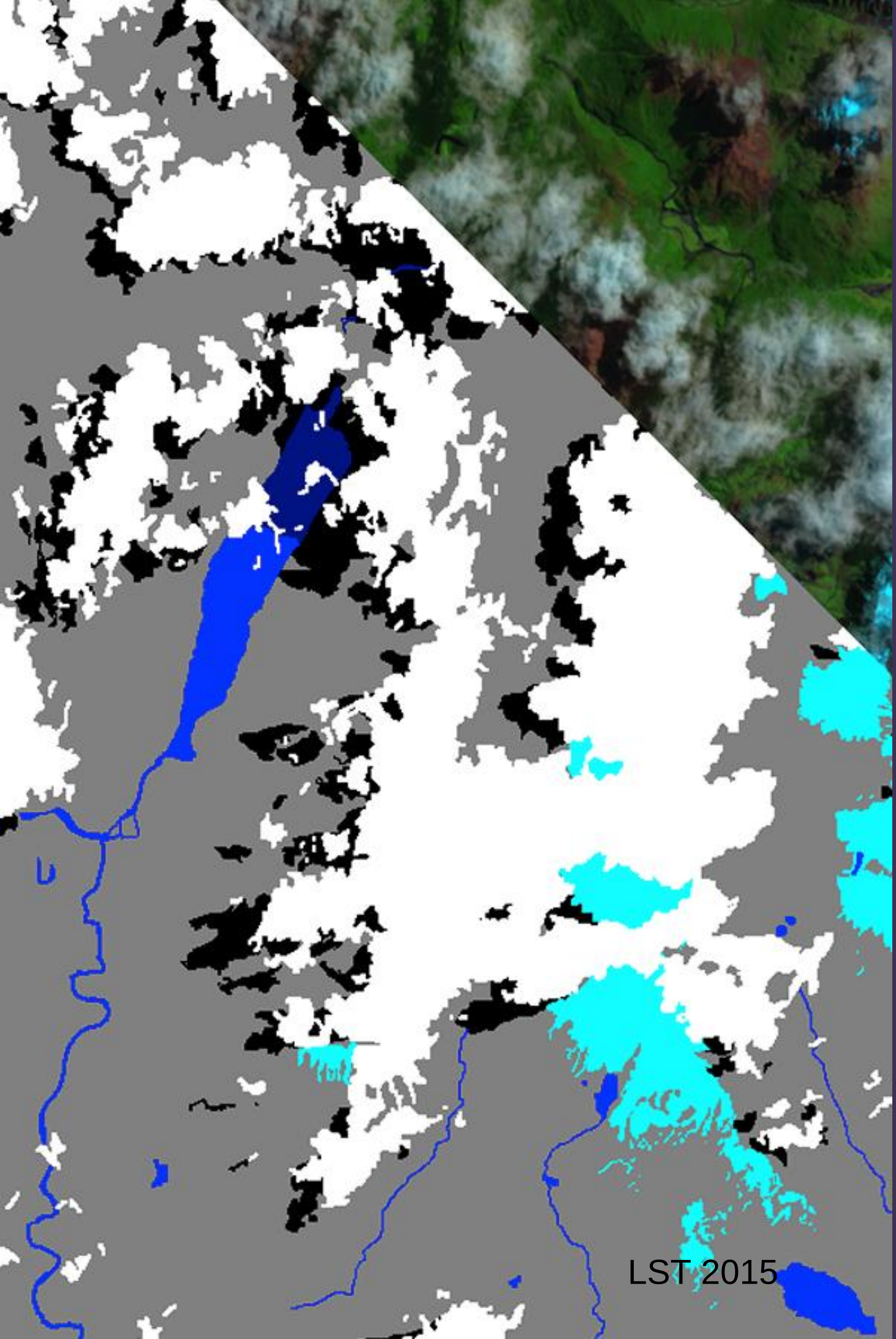


1000×1000 pixel sub-scenes from 65 OLI/TIRS scenes

1 from each Biome on each Continent

+ 12 additional sub-scenes for testing





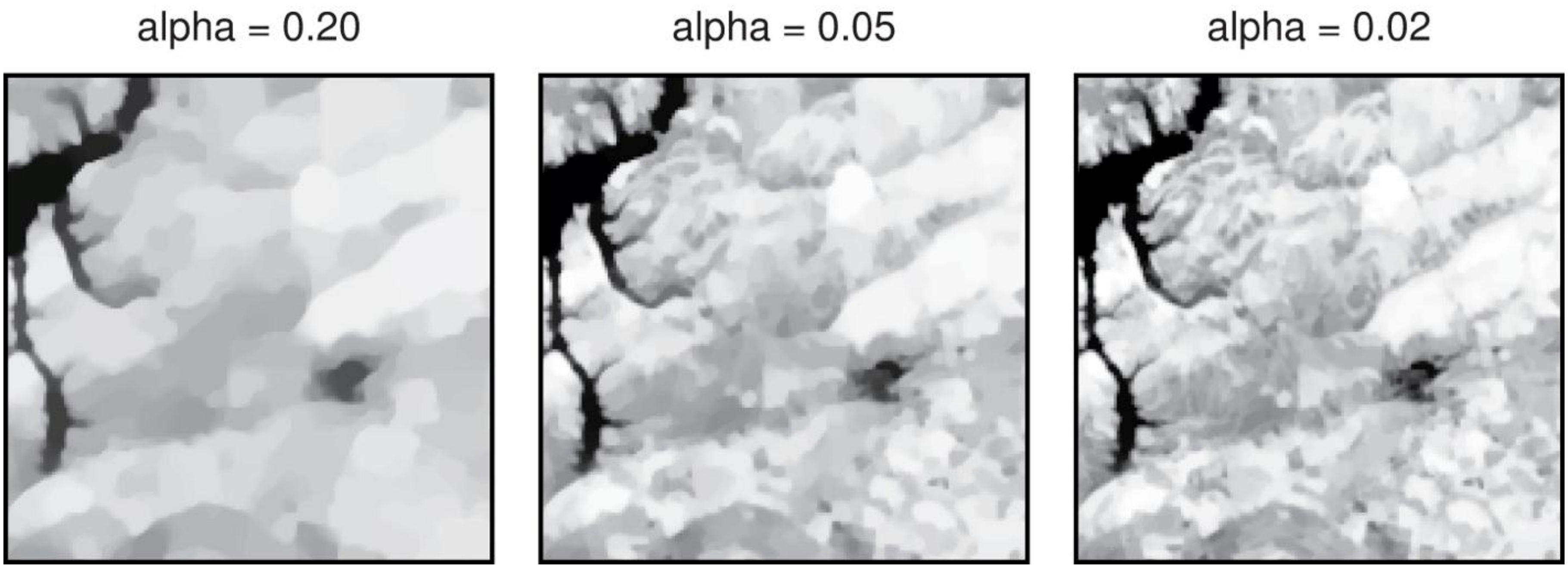
Dataset of human-classified obstruction with classes for:

- Clear-sky
- Clouds
- Cloud-shadow
- Cloud-shadow over water
- Water
- Flood
- Ice / Snow

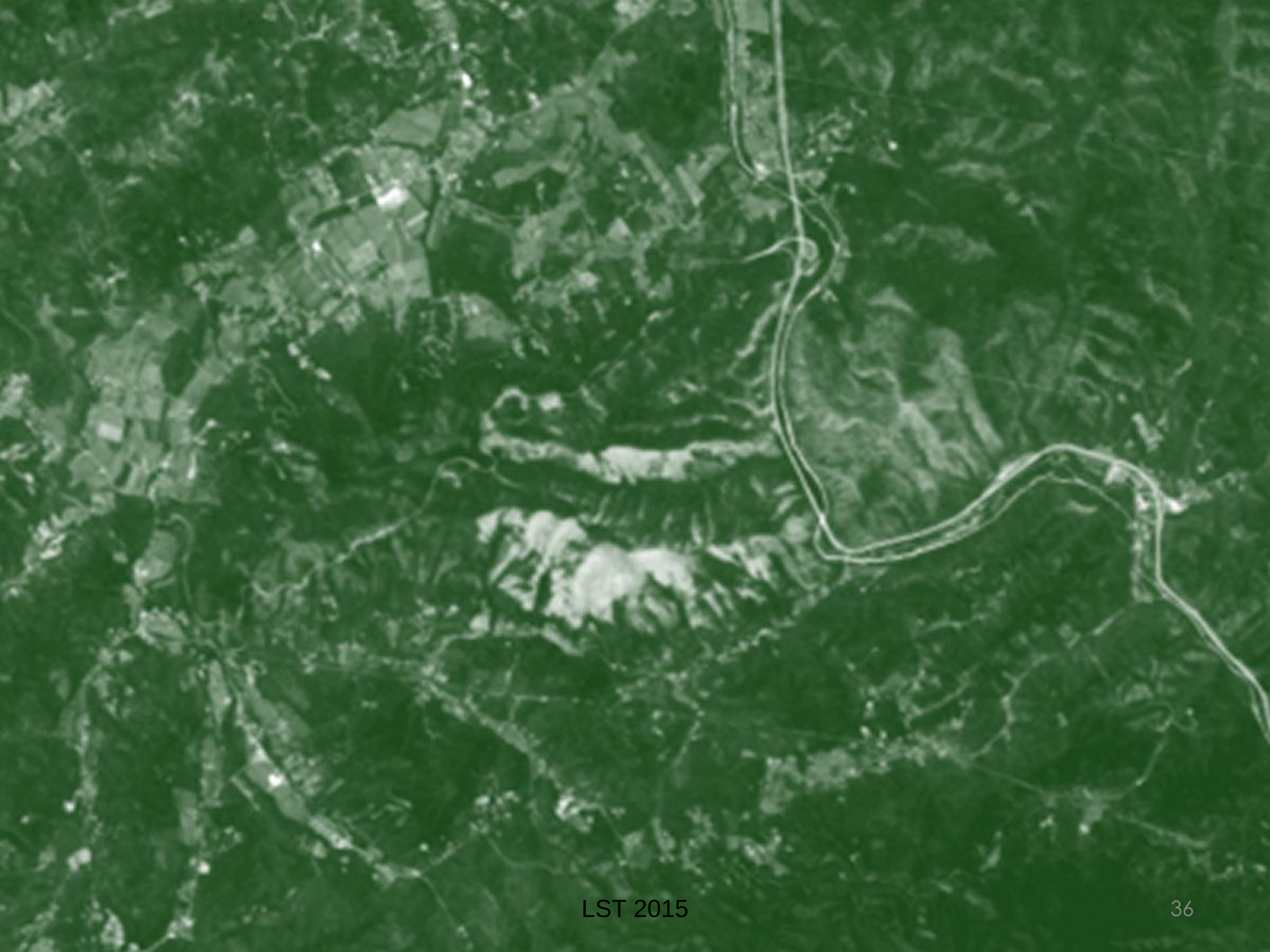
Future directions

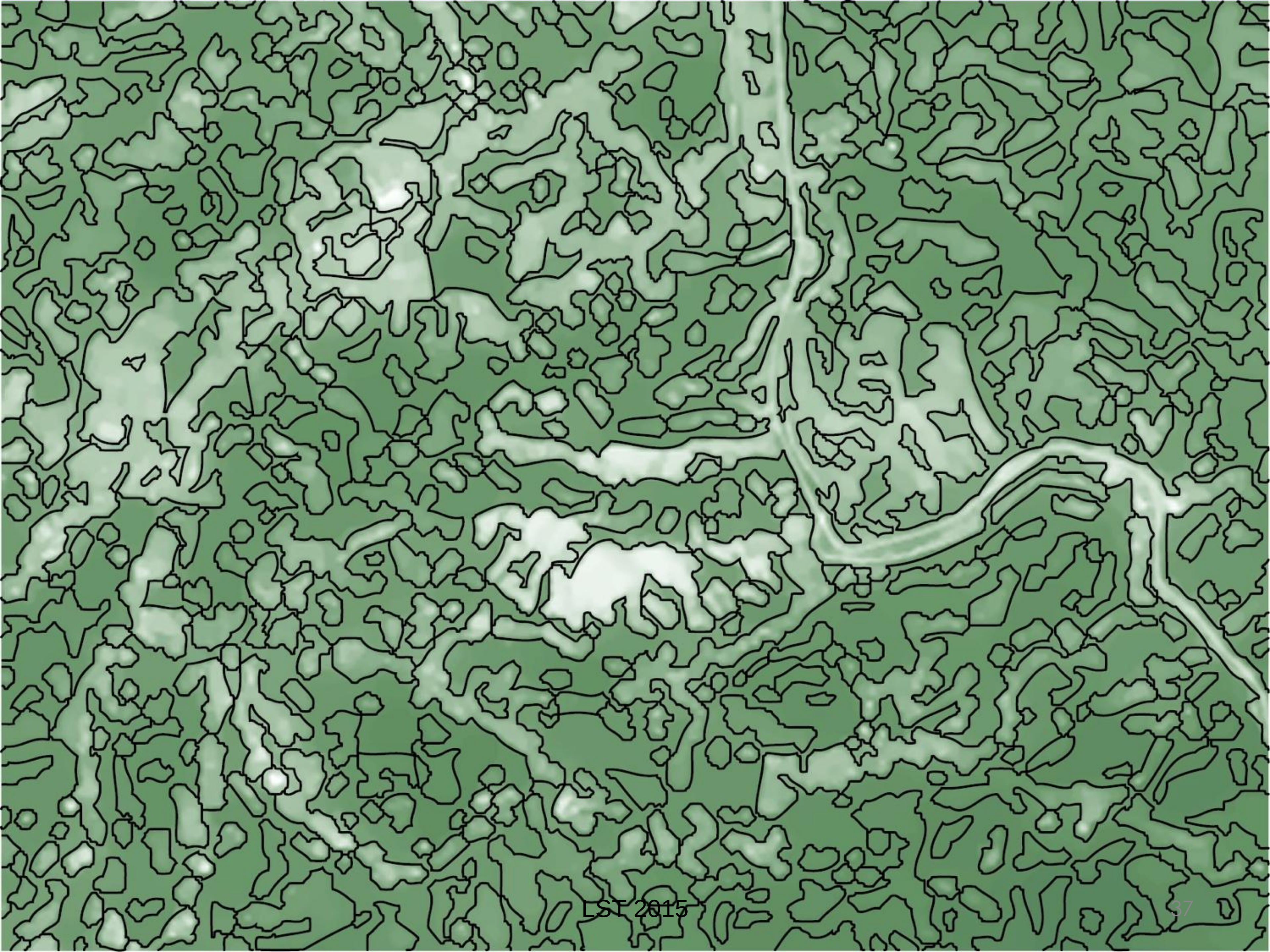
1. Add phenologically important dates (**Spring**)
2. Quantify tradeoff between simplicity & accuracy
1. Improve L8 cloud masking
2. Include **patch** characteristics: Size, Shape, Texture

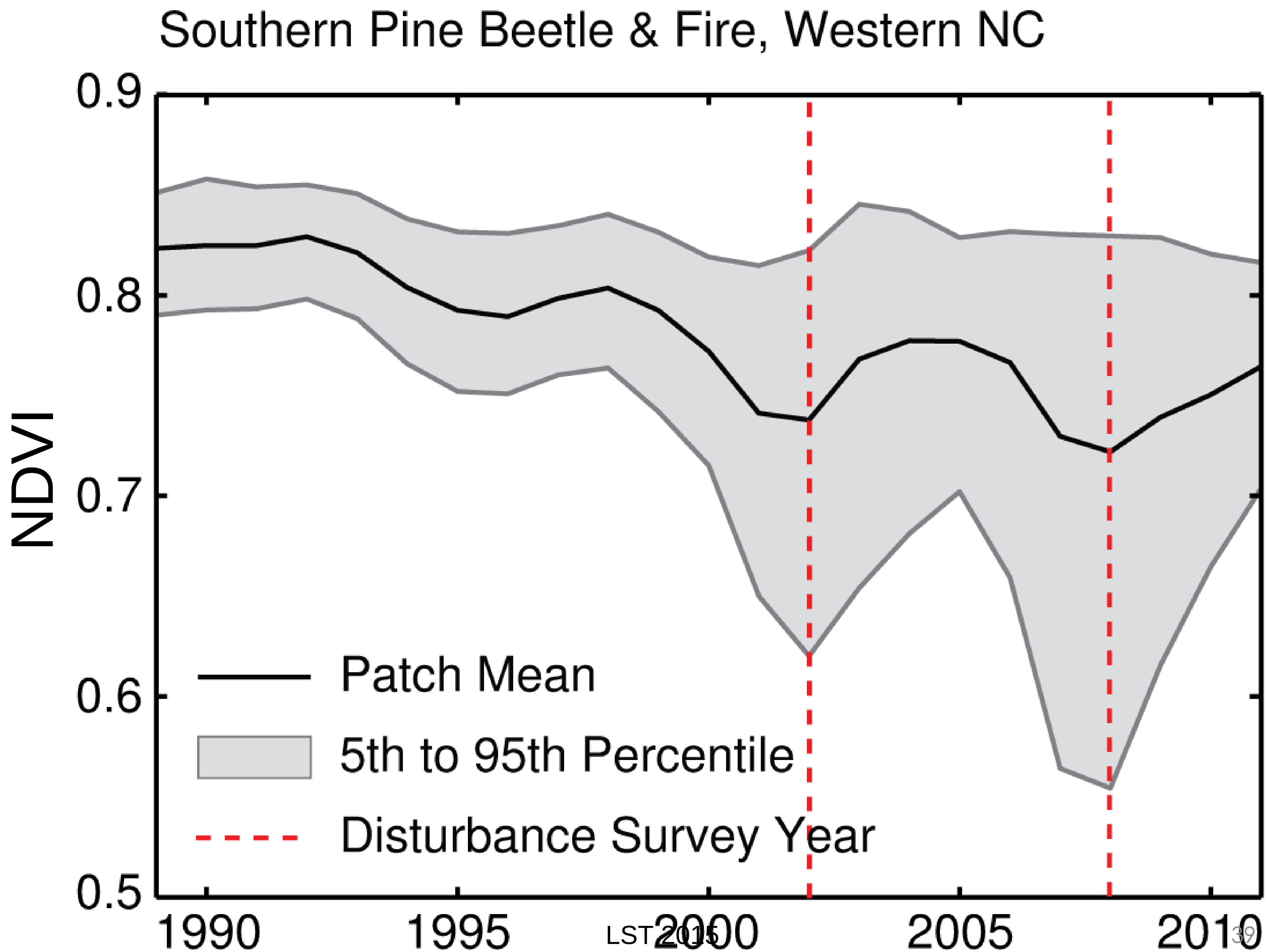
Patch-based Approach



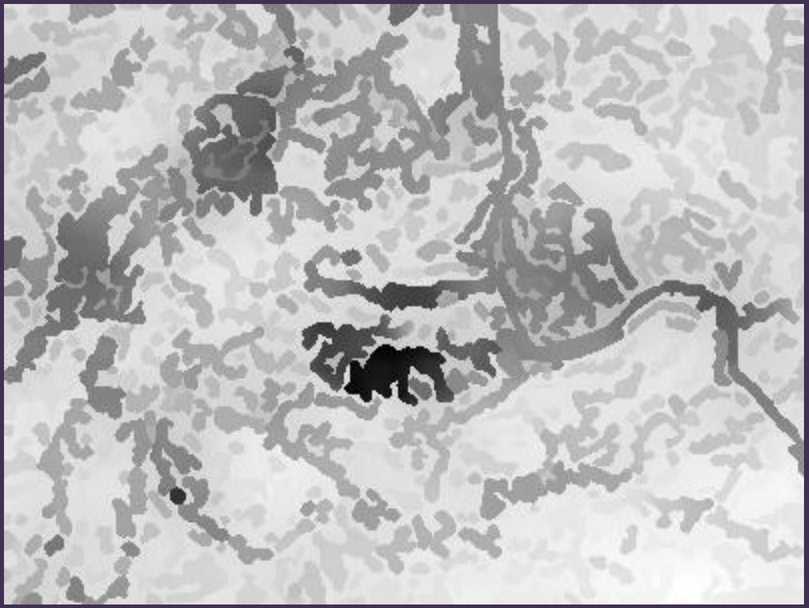
VeRDET:
Vegetation Regeneration and Disturbance Estimates through Time



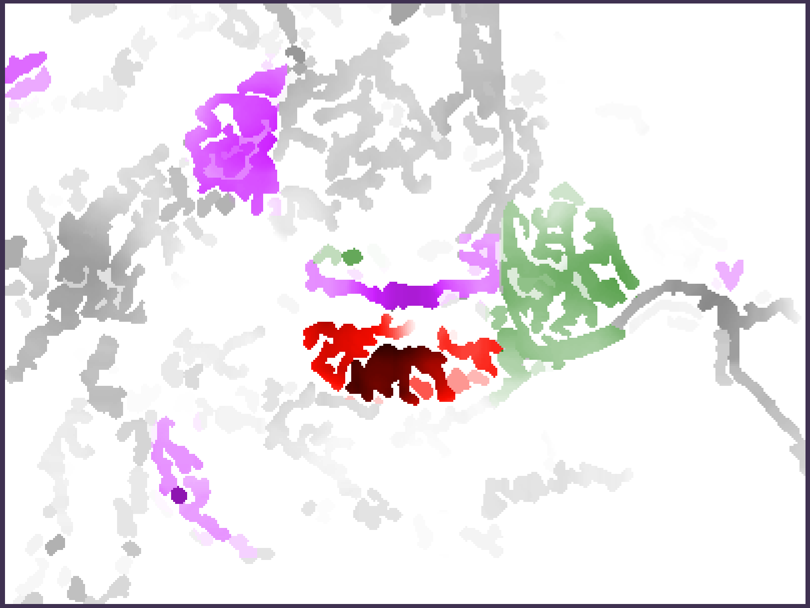



Southern Pine Beetle & Fire, Western NC
NDVI
0.9
0.8
0.7
0.6
0.5
1990
1995
2000
2005
2010
Patch Mean
5th to 95th Percentile
Disturbance Survey Year

Vegetation Index



Patch Mean



Find (and classify) Changes

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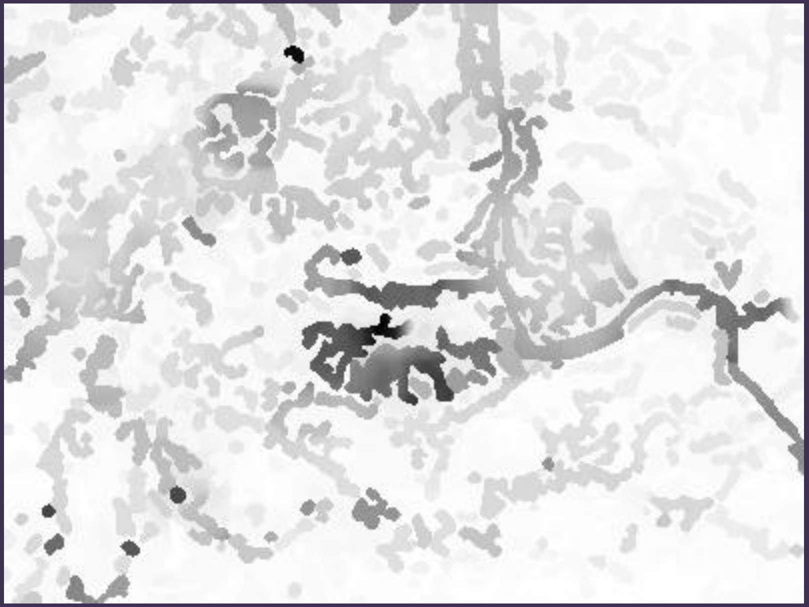


Patch Variance

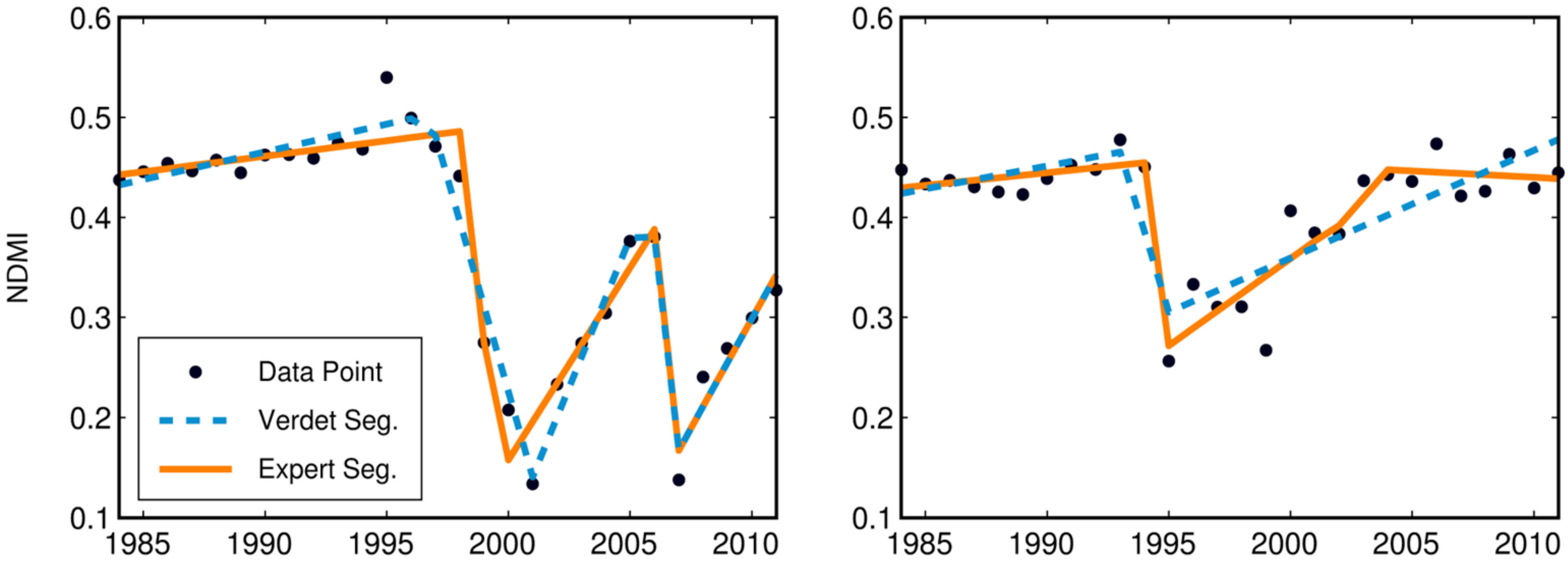
Conclusions

- Land cover and change can be harmonized, but there are challenges
- Land cover classes must be sensitive to spectral properties
- Ongoing approaches to improve:
  - Continue improving cloud mapping
  - Incorporate spatial context
  - Formalize mathematical cohesion between spatial and temporal segmentation

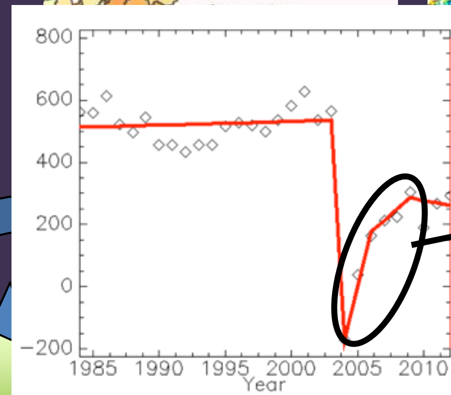
Thanks….

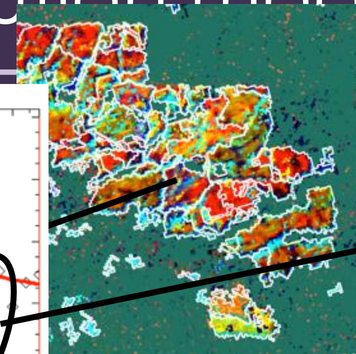
Backup slides

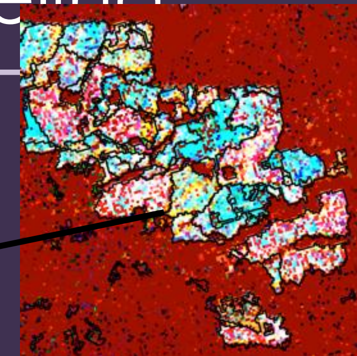
Similar Goals to LandTrendr



Framework for attribution modeling





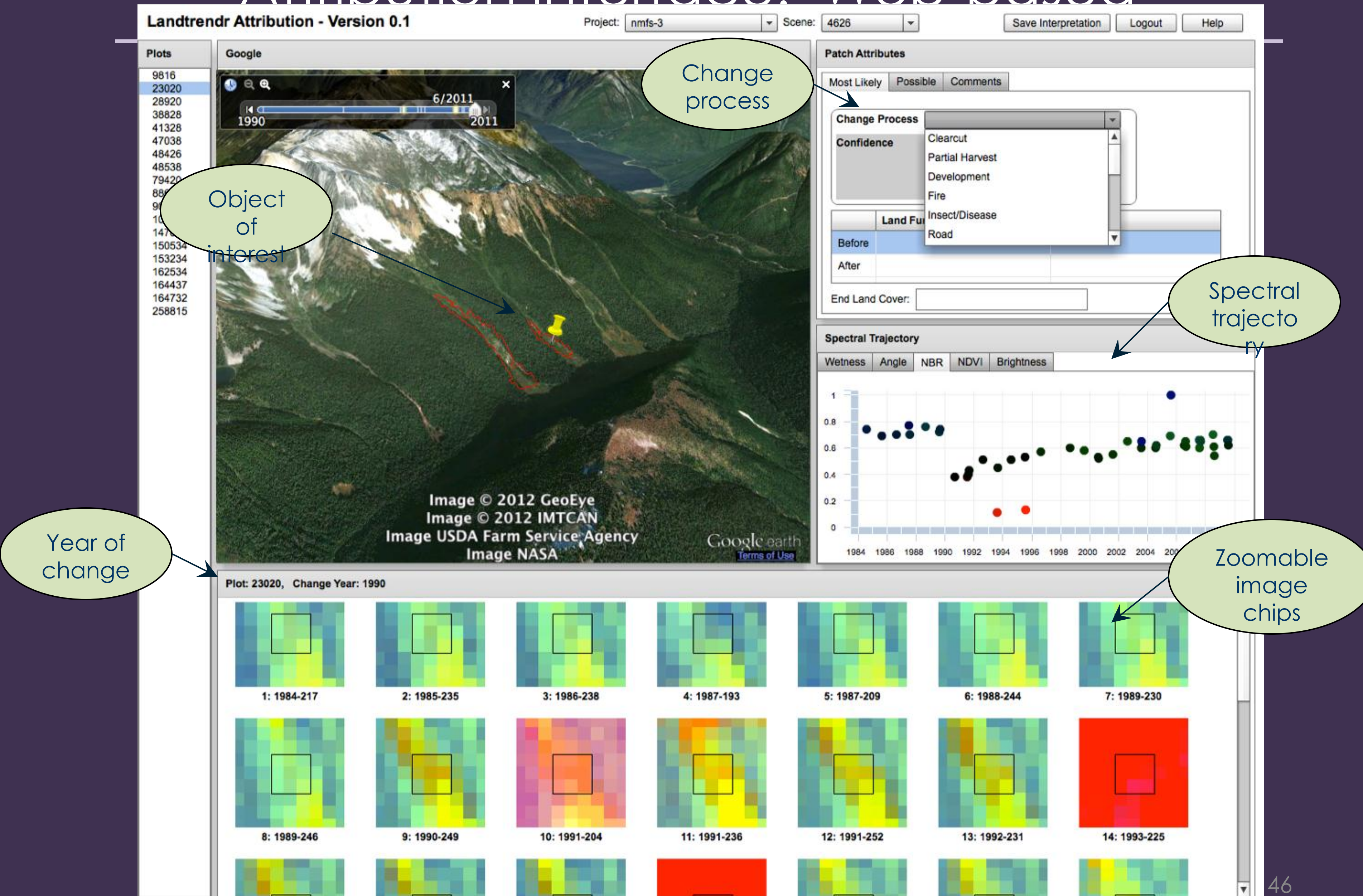


Pixel

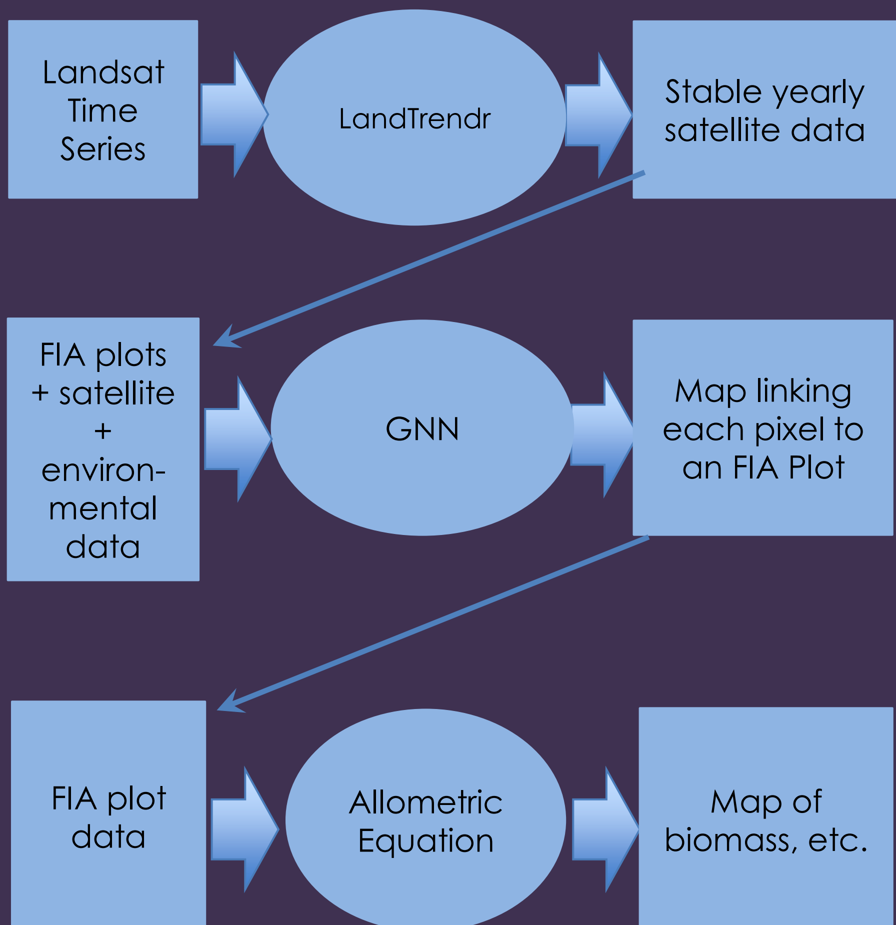
Map: Pixels of change

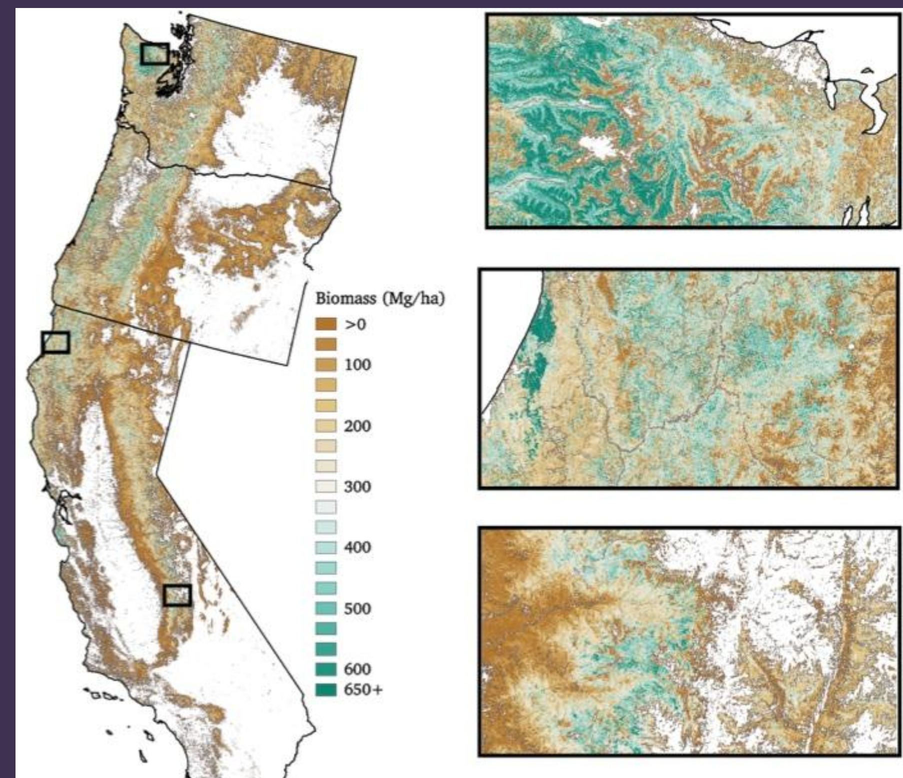
Filter to minimum mapping unit, make polygons

Attribution interface: Web-based

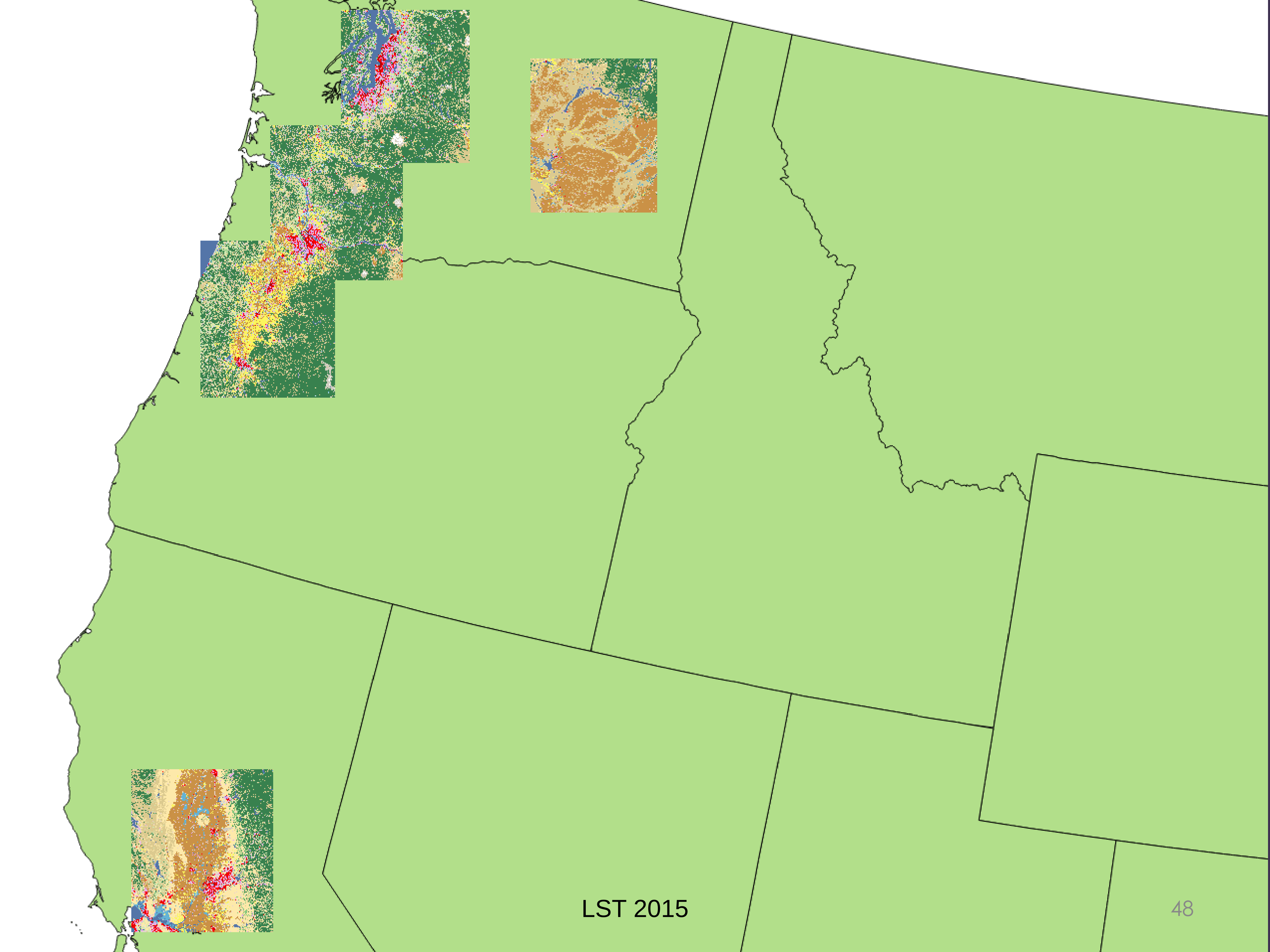


Product: Yearly Tree Live Biomass





Mean aboveground tree biomass (yr. 2000)



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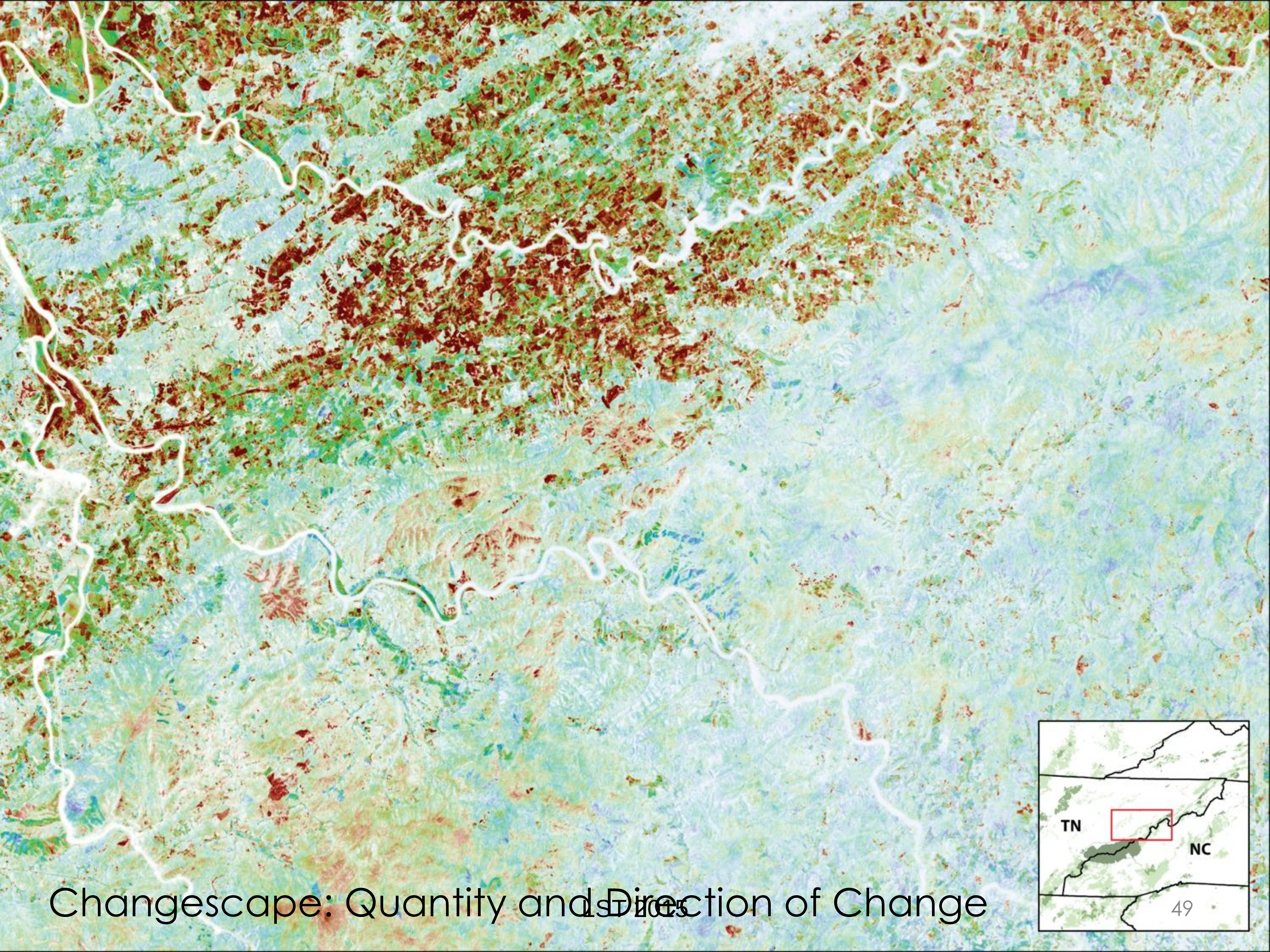


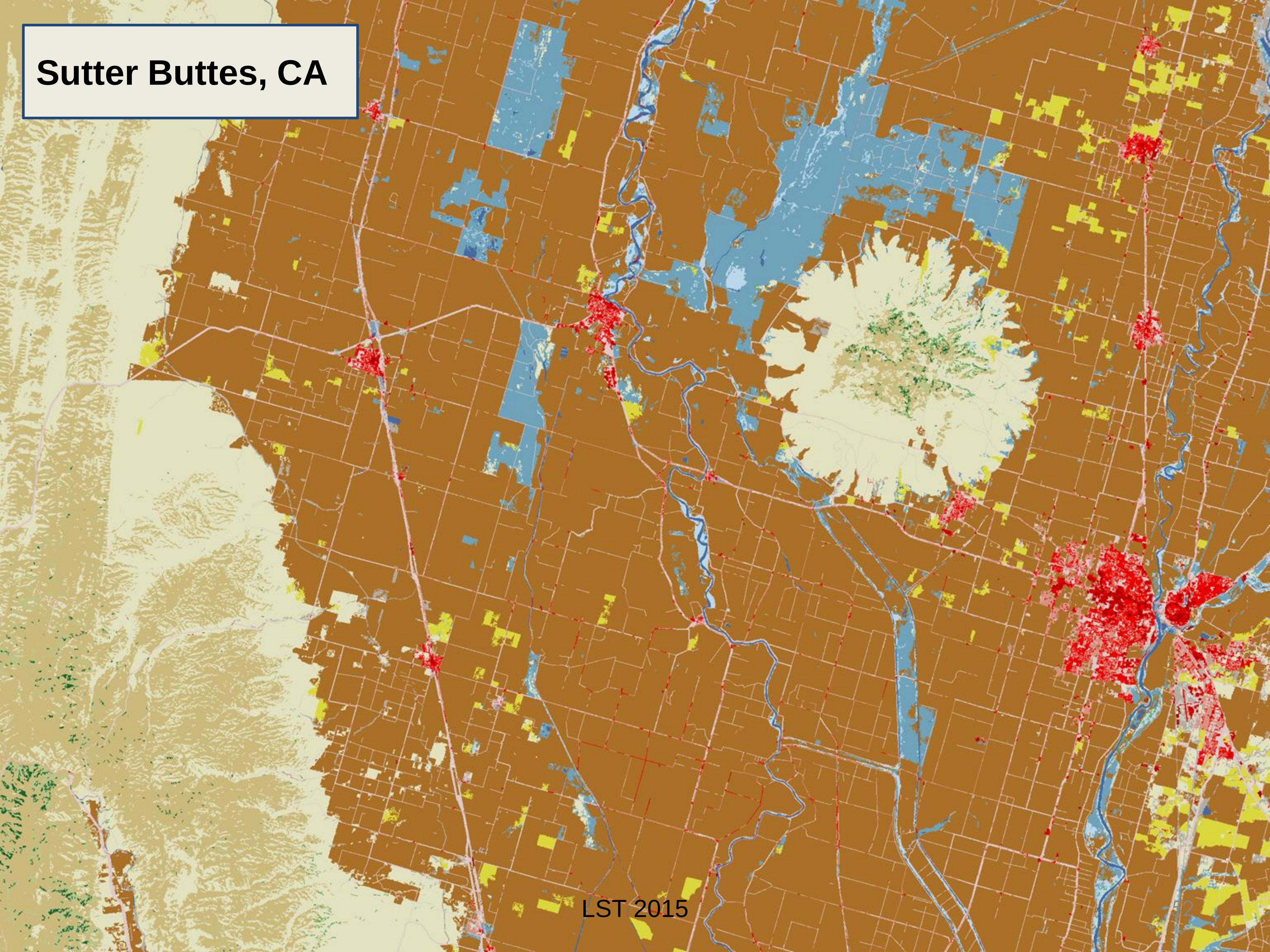
Changescape: Quantity and Direction of Change

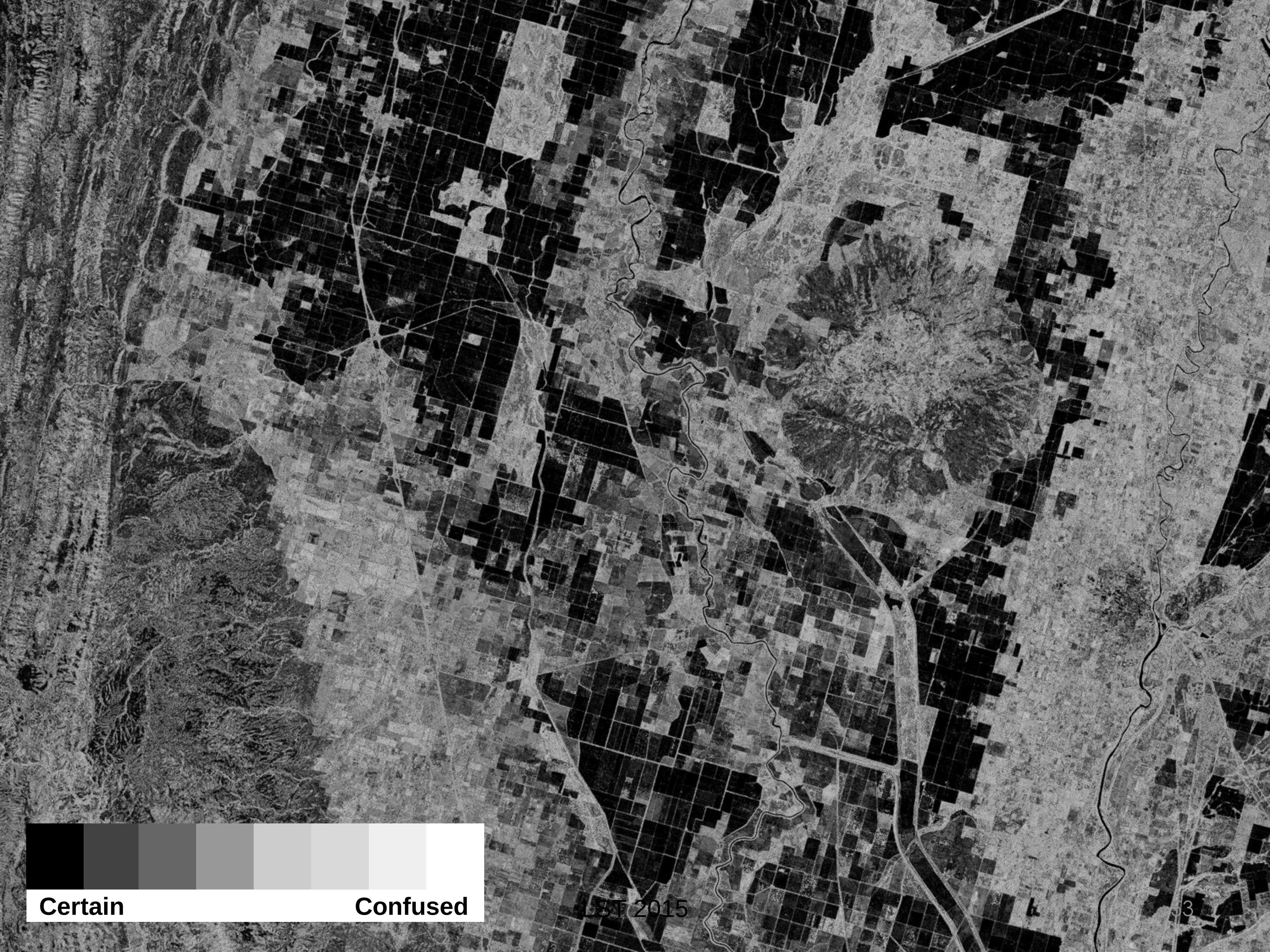
Adding Spring Scenes

	Eastern Washington				Western Washington & Oregon				California Central Valley		
	Spring	**1995**	**Change**		**Spring**	**1995**	**Change**		**Spring**	**1995**	**Change**
Open Water	90.8	90.7	0.1		92	89.9	2.1		91.6	87.1	4.5
Ice / Snow					84	81.6	2.4				
Developed, Open	15.3	12	3.3		6.4	5.3	1.1		8.9	8.9	0
Developed, Low	41.7	43.5	-1.8		45.3	41.4	3.9		36.2	29.6	6.6
Developed, Medium	47.2	40.9	6.3		56.5	54.2	2.3		58.7	51.9	6.8
Developed, High	41.1	46.6	-5.5		70.9	61.4	9.5		74.5	66.5	8
Barren	**58.5**	**34.8**	**23.7**		**43.3**	**28.5**	**14.8**		**24.4**	**17.8**	**6.6**
Forest, Deciduous	**22.7**	**11.3**	**11.4**		**33.2**	**30.2**	**3**		**39.5**	**30.3**	**9.2**
Forest, Evergreen	91.8	92.3	-0.5		84.4	83.8	0.6		74	69.9	4.1
Forest, Mixed	0	2.6	-2.6		46.1	43.7	2.4		26.4	24	2.4
Shrub/Scrub	84.8	84.7	0.1		49.2	50.6	-1.4		60.8	54.8	6
Herbaceous, Grassland	36.5	31.7	4.8		40.3	35.1	5.2		77.9	76.9	1
Pasture/Hay	**46.4**	**40.7**	**5.7**		**59.9**	**56.1**	**3.8**		**40.9**	**27.3**	**13.6**
Cultivated Crops	85.2	84	1.2		32.2	31.9	0.3		74.9	71.4	3.5
Wetlands, Woody	23.5	18	5.5		13.8	16.7	-2.9		32.5	15.4	**17.1**
Wetlands, Emergent	**33.9**	**23.5**	**10.4**		**5.8**	**4.7**	**1.1**		**27.1**	**4.5**	**22.6**

Can spatial pattern of error yield insight?

Sutter Buttes, CA





Certain
Confused

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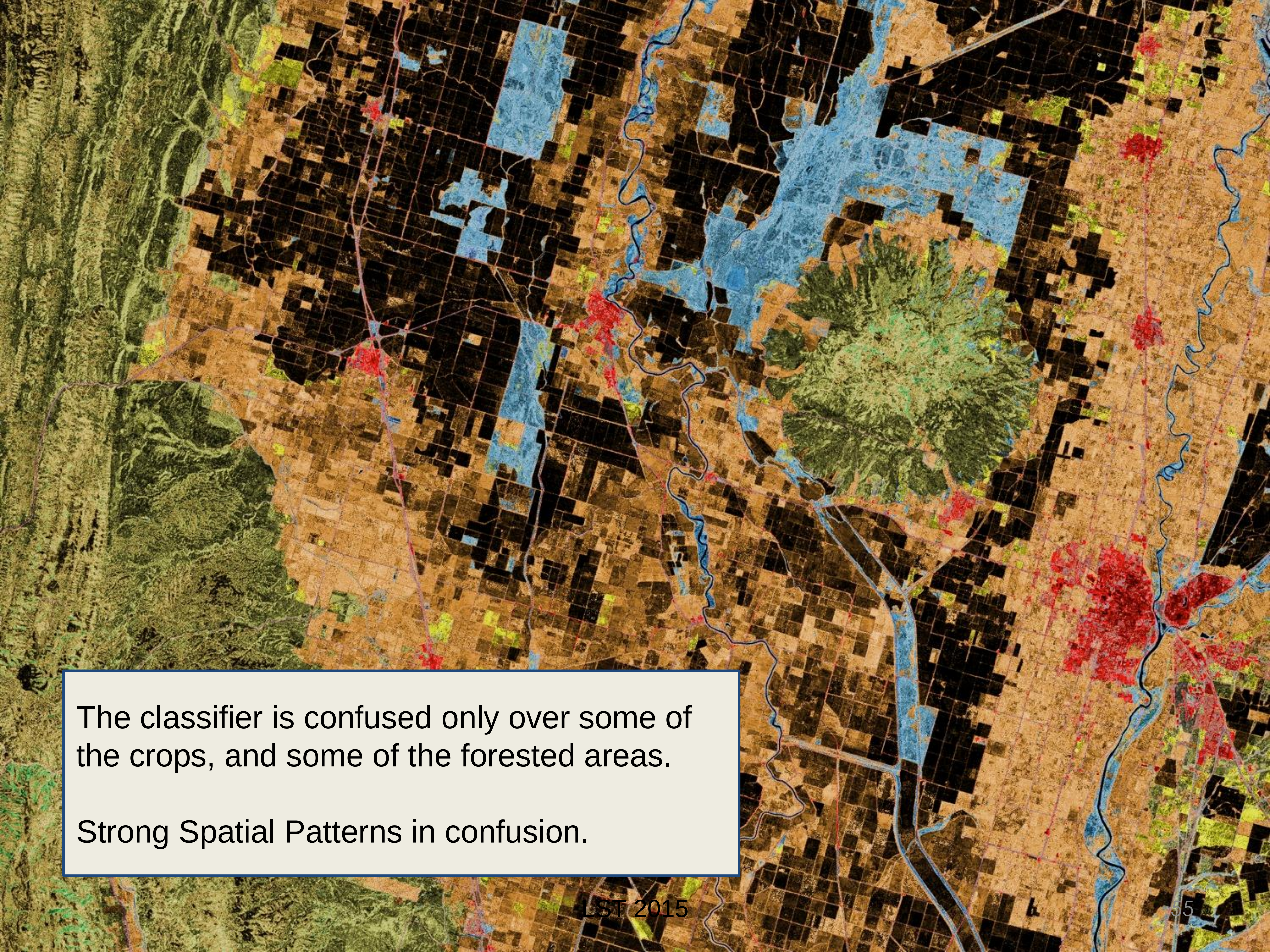

The classifier is confused only over some of the crops, and some of the forested areas.

Strong Spatial Patterns in confusion.